Deep Learning Solution for Medical Imaging Challenges

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Abstract: - Medica imaging plays a crucial role in diagnosis and treatment planning. However, the large volume and high resolution of images like CT, MRI and X-rays create storage and transmission challenges, especially in telemedicine ans resource-constrained environments. Traditional Compression methods (e.G. JPEG, JPEG2000) often fail to maintain diagnostic quality, prompting the need for advanced approaches. With the rise of artificial intelligence, deep learning-based compression offers promising results in preserving critical images features while significantly reducing file size. Deep learning-based compression techniques, especially CNNs and GANs represent a significant advancement in medical image storage and transmission. Additionally, inference time and computational requirements were analysed to retain diagnostic fidelity, making them highly suitable for telehealth, archiving and mobile diagnostics. Future work can explore hybrid models and integration with PACS systems for clinical deployment.

Keywords*: Medical Image Compression, Deep Learning, Autoencoders, CNN, GAN, PSNR, SSIM, Telemedicine, Diagnostic Imaging.*

1. Introduction

Medical imaging technologies like MRI (Magnetic Resonance Imaging), CT (Computed Tomography), and X-ray imaging have transformed healthcare by allowing diagnosis and testing of thousands of diseases non-invasively, as per Toderici et al. (2017) [1]. But these modalities produce massive amount of high-resolution data causing problems with storage, transmission and processing. Thus, it is essential to have efficient compression techniques to accommodate the ever-increasing demand of medical image storage and communication without sacrificing critical diagnostic information. While traditional methods for image compression are powerful, their quality may suffer, or they may exhaust too much time or memory for a large enough dataset. Recently, deep learning has proven to be a transformative solution to learn very complex patterns for highly efficient as well as adaptive, and intelligent compression (Vuille-dit-Bille et al. 2022) [12]. Image compression has achieved promising results through deep learning such as convolutional neural networks (CNNs), autoencoders, variational autoencoders (VAEs) and generative adversarial networks (GANs). Such models can learn automatically data-driven representations which are compact and high fidelity. This is unlike traditional codecs which cannot be optimized for specific medical imaging modalities and can sometimes not even adapt adaptively to different resolutions and imaging protocols or even patient specific variations (Pang et al. 2021) [6]. Recent innovations include:

Autoencoder-based Compression: Learning low-dimensional encodings that reconstruct images accurately.

Adversarial Training: Using GANs to enhance perceptual quality during decompression.

Loss Function Optimization: Custom loss functions to preserve fine diagnostic details rather than just pixel-wise accuracy.

Background

Computed tomography (CT), X-rays, and magnetic resonance imaging (MRI) are examples of medical imaging technologies that are essential for both diagnosing and tracking a variety of illnesses. High-resolution images produced by these modalities offer the fine details required for precise medical interpretation. The vast amount of visual data produced, however, presents serious problems with regard to transmission, storage, and real-time accessibility, particularly in resource-constrained environments, telemedicine, and mobile diagnostics. Conventional image compression techniques such as JPEG and JPEG2000 are frequently used, however when applied to high compression ratios, they frequently lose diagnostic information. With the ability to strike a balance between file size reduction and image fidelity, the development of artificial intelligence—specifically, deep learning-based models—has created new opportunities for intelligent, adaptive, and efficient image compression.

Compression methods that lower storage and transmission costs without sacrificing the vital diagnostic information necessary for patient care are needed to meet the growing demand for medical imaging data. Accurate diagnosis may be hampered by the distortions and loss of subtle picture structures that traditional compression techniques experience at high compression settings. Additionally, there are issues with current deep learning techniques, including large computing costs, poor cross-modal generalization, and a lack of clinical validation. Advanced techniques that guarantee large compression ratios while maintaining diagnostic accuracy, guaranteeing real-time application, and adhering to clinical and data protection regulations are desperately needed.

Proposed Method

Using Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Convolutional Neural Networks (CNNs), this study suggests deep learning-based medical picture reduction models. The NIH Chest X-ray Dataset, the BraTS brain tumor MRI dataset, and The Cancer Imaging Archive (TCIA) are among the publicly accessible and anonymized datasets used to train the models. To guarantee both diagnostic quality and computational efficiency, the models are assessed using metrics including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Compression Ratio (CR), bits per pixel (bpp), and inference time.

2. Literature Review

The literature review has been conducted to gain a comprehensive understanding of the current state of medical image compression and the challenges it presents. By examining recent advancements and existing limitations, this review underscores the need for smarter, more efficient, and clinically reliable compression techniques that can address the increasing demands of modern healthcare.

As such, CT, MRI, and X-rays generate huge amounts of high-resolution images and are crucial for forthright diagnosis and treatment planning. These large datasets are difficult to manage, transmit and store. However, traditional compression techniques are also helpful in compacting the image but can also adversely affect the image quality and often lose diagnostically critical information. In recent years, deep learning has proven to be a powerful tool for acquiring high compression rates along with retaining key visual and diagnostic details of medical imaging.

Medical Image Compression: Why It Matters?

Although CT, MRI, and X-ray pictures are essential for diagnosis, their large data volumes put a burden on transmission and storage. Conventional compression techniques, such as JPEG and JPEG2000, either generate artifacts that can impact diagnosis or lose crucial information. These formats are used by DICOM and other standards, however they are not suitable for high compression. Because even minor distortions can result in incorrect diagnoses, it is imperative to preserve every little detail. Smarter solutions are essential in light of tighter rules and expanding 3D image datasets. Deep learning can help with that by providing strong, flexible compression methods that preserve image quality while addressing the difficulties of contemporary healthcare.

Smart Compression for Smarter Healthcare

Using cutting-edge technologies like autoencoders, CNNs, and GANs, deep learning is revolutionizing the compression of medical pictures by achieving high compression rates without sacrificing important features. These AI-powered algorithms are perfect for complex medical data since they automatically figure out the optimal methods to encode and rebuild images. Research has already demonstrated remarkable outcomes, such as improved texture restoration in pathology scans and chest X-rays that meet conventional compression norms. However, there are still issues including high processing demands, a lack of training data, and the requirement for thorough clinical testing. The way forward is to provide scalable, dependable, and effective systems that make sure compressed images are both diagnostically ready and storage-friendly.

Traditional Image Compression Techniques

Toderici et al. (2017) It stated that compression methods are usually divided into two main categories lossless and lossy compression [2]. Lossless techniques maintain the material data at original without any information lost, which is vital to some particular sensitive medical applications; lossy compression methods hold greater information reduction rates, however with the expense of some image quality decay [3]. For example, common lossless methods are PNG or Huffman coding; lossy include JPEG and JPEG2000. JPEG2000 has clearly shown a significant advantage over the traditional JPEG in terms of better image quality at lower bits' rate, but it does introduce artifacts when the compression rate is pushed to its extremely high limits. Furthermore, these artifacts might distort clinical diagnosis and interpretation, and traditional lossy methods are limited for sensitive applications like medical imaging [4].

In the case of healthcare, the goal of the DICOM (Digital Imaging and Communications in Medicine) standard naturally includes compression formats like JPEG Lossless or JPEG2000. Although this progress has been made, it has been shown that compression standards have been historically suboptimal in preservation of subtle clinical features when very high compression ratios are needed [5]. However, the necessity has compelled the researchers to look for different ways to get the use out of data including deep learning-based methods that surpass the shortcomings of traditional approaches. In comparison with the ordinary photographic images, the compression of the medical images requires to be more rigorous. The most important challenge is to preserve diagnostic features because even tiny distortions might induce severe misinterpretations or misdiagnoses [6]. Additionally, there are numerous regulatory standards and clinical guidelines that require the medical images to be absolutely intact, restricting to some extent, the level of acceptable image manipulation. Another major challenge of medical image processing is the vast volume of medical imaging data, especially of the recent 3D imaging modalities such as MRI and PET scans [7]. Such challenges emphasize the need for innovative compression solutions that enable the delivery of high compression ratios while avoiding the degradation of image quality and its diagnostic value.

Deep Learning: Redefining Medical Image Compression

Revolutionary changes in the field of image compression are brought by deep learning techniques that are based on autoencoders, convolutional neural networks (CNNs), and generative adversarial networks (GANs). Neural networks of the autoencoder class learn efficient low dimensional representations of data and can reconstruct the original input through such compact representations [8]. An end-to-end optimized method of deep learning based using generalized divisive normalization layers, which yielded superior results to classical JPEG and JPEG2000, particularly at lower bitrates, was demonstrated by Ballé et al. (2017) [3]. With their hierarchical feature extraction capabilities, CNNs have proven in principle effective for learning spatially adaptive representation for medical images. Unlike hand crafted methods, the optimal encoding and decoding strategies are automatically learnt in CNN while training, making them well suited to high complexity and subtlety in medical data. A new probabilistic framework for latent space representation within traditional autoencoder frameworks, Variational Autoencoders (VAEs), also further enhance upon these models in order to obtain better generalization across different imaging datasets (Kingma and Welling, 2014) [4] [13].

The field of image compression through GANs as a method for preserving visual quality has also been investigated. GAN models rely on two components to create a generator that produces compressed results which a discriminator evaluates to distinguish real images from generated ones. GANs recognize adversarial training to produce detailed textured reconstructions with increased perceptual quality that matters for medical data analysis of texture details (Rippel and Bourdev, 2017) [8]. Deep learning models have proven effective for medical image compression through multiple successful applications reported during recent times. Restoration of diagnostic features using deep models for compressing histopathological images demonstrated superior performance compared to traditional techniques yet achieved clinical usability according to Rajpoot et al. (2020). The researchers at Torbati and Lee (2021) established a CNN system for chest Xray image compression which produced SSIM ratings equivalent to JPEG2000 standards at equivalent compression levels. Experimental results demonstrate deep learning techniques provide high compression ratios while causing minimal effect on medical image clinical quality which represents crucial aspects for transforming healthcare through practical deployment [9] [10].

Table 1: Medical Image Compression – Methods, Challenges, and Emerging Needs

Aspect	Details
Types of Compression	Compression methods are usually divided into two categories: Lossless and Lossy.
Lossless Compression	Maintains the original data without any information loss. Vital for sensitive medical applications. Examples: PNG, Huffman coding.
Lossy Compression	Achieves higher information reduction rates at the cost of some image quality decay. Examples: JPEG, JPEG2000.
Advantages of JPEG2000	Provides better image quality at lower bitrates compared to JPEG.
Limitations of JPEG2000	Introduces artifacts at high compression rates that may distort clinical diagnosis and interpretation, making it unsuitable for sensitive medical imaging.
DICOM Standards	Healthcare compression formats include JPEG Lossless and JPEG2000, but these have historically been suboptimal in preserving subtle clinical features at very high compression ratios.
Need for Better Solutions	Researchers are exploring deep learning-based methods to surpass the limitations of traditional compression approaches.
Challenges in Medical Imaging Compression	Medical image compression must be more rigorous than ordinary photographic images. - Tiny distortions can lead to misinterpretations or misdiagnoses. - Regulatory standards require images to be intact, limiting acceptable manipulations. - The vast volume of data, especially from 3D modalities like MRI and PET scans, demands innovative compression solutions.
Goal	Enable high compression ratios while preserving image quality and diagnostic value.

Mesh displays limited potential despite its potential in medical image compression solutions. The high computational demands which occur during both training and inference create barriers for deploying medical imaging systems in low-resource environments including rural clinics and emergency situations [12]. The effectiveness of models depends strongly on the datasets because training with restricted or uniform datasets limits their ability to adapt to different demographic populations of patients. Deep learning-based compression models need additional clinical testing because their validation process remains in its developmental phase. Thorough validation and testing procedures should be performed to prevent the loss of crucial diagnostic details with AI-driven compression systems since this could lead to medical and ethical problems about AI-driven compression's reliability. Most deep learning platforms conduct their operational tests using natural images from databases such as ImageNet instead of medical imaging databases. Research on medical image compression evaluation lacks standardized benchmarks that cause assessment between different studies to become difficult [14]. The medical community requires immediate development of compression models that simultaneously achieve both optimal compression ratios combined with low processing delays as well as precise reconstruction output fit for clinical needs [15].

3. THEORETICAL FOUNDATIONS

Neural networks are cascaded layers of nodes (neurons) where each node takes input, uses weighted input and biases, and uses a non-linear activation function. The specific neural network we use for unsupervised learning of efficient data codings are autoencoders. Finally, the network is trained to reconstruct its input at the output layer and therefore learns compressed representations (encodings) of the data by itself (Ballé et al. 2017) [2]. They are very commonly employed for image compression as they have the ability to learn how to remove redundancies.

VARIATIONAL AUTOENCODERS (VAES) AND GENERATIVE ADVERSARIAL NETWORKS (GANS)

Both VAEs and GANs are advanced architectures that are useful in image generation and compression.

A. Variational Autoencoders (VAEs)

VAEs introduce a probabilistic twist to traditional autoencoders by modelling the latent space as a probability distribution rather than fixed vectors. This allows for smoother interpolation between compressed representations and better generalization.

Variational Autoencoders (VAEs) represent deep learning models that combine graphical probabilistic models according to Kingma and Welling (2014). The fundamental difference between a standard autoencoder lies in its ability to find a deterministic input-to-latent-space mapping because VAEs require latent variables to emerge probabilistically from distributions most commonly Gaussian [16] [17]. The encoder generates parameters of distribution (mean and variance) instead of producing a static vector.

Key Concepts of VAEs:

Latent Space Regularization: Instead of mapping input data to a single point in latent space, VAEs map it to a probability distribution. During training, latent variables are sampled from these distributions, encouraging the latent space to be continuous and structured [18].

Reconstruction Loss and KL Divergence: The VAE objective is twofold:

Reconstruction Loss: Ensures that the decoded output is similar to the input.

Kullback-Leibler (KL) Divergence: Ensures that the learned distribution remains close to a standard normal distribution.

Advantages in Medical Image Compression:

- Smooth Latent Space: The continuous nature of the latent space makes VAEs particularly robust for encoding complex medical images.
- Sampling Capability: VAEs allow new images to be generated by sampling from the latent space, which can help in data augmentation or reconstructing missing parts.

Limitations:

- Blurry Reconstructions: Due to the probabilistic averaging during training, VAE-generated images may be blurrier compared to GAN-generated images.

B. Generative Adversarial Networks (GANs)

GANs consist of two networks (a generator and a discriminator) that are trained adversarially. For compression, GANs can be used to improve the realism of reconstructed images even when using high compression rates. GANs, proposed by Agustsson and Timofte (2017), are a class of deep generative models where two neural networks — the generator and the discriminator — are trained simultaneously through an adversarial process [19].

Architecture:

- Generator (G): Takes random noise (or latent representation) as input and produces synthetic images.
- Discriminator (D): Tries to distinguish between real images (from the training dataset) and fake images (produced by the generator).

Applications in Image Compression:

Instead of simply minimizing reconstruction loss, GANs ensure that reconstructed images "look real" by fooling the discriminator.

GANs can generate sharper and more detailed reconstructions, critical for medical images where visual fidelity impacts diagnostic decisions.

Advantages in Medical Image Compression:

- High-Quality Reconstructions: GANs outperform traditional methods in generating sharper and perceptually convincing images.
- Data Distribution Modelling: GANs learn the underlying distribution of medical images, leading to better generalization.

Limitations:

- Training Instability: GANs are notoriously difficult to train due to issues like mode collapse and non-convergence.
- Resource-Intensive: Requires more careful tuning of hyperparameters and more computational power compared to VAEs or standard autoencoders.

This chapter established the theoretical underpinnings necessary for understanding how deep learning techniques can be effectively applied for medical image compression. It covered fundamental concepts, advanced architectures like VAEs and GANs, and standard evaluation metrics, forming a strong foundation for the subsequent experimental design and implementation.

4. RESEARCH METHODOLOGY

RESEARCH DESIGN

The research implements an applied experimental quantitative study method for deep learning technique development in medical image compression. The research evaluates the effectiveness of deep learning techniques to compress images and determines their ability to enhance image quality levels over traditional methods. The research initiative involved medical imaging data collection together with deep learning model-based preprocessing and modeling before training and evaluation of the data [20].

Public and ethical datasets which served to obtain medical images consisted of the NIH Chest X-ray Dataset (Wang et al., 2017) and BraTS brain tumor MRI dataset and The Cancer Imaging Archive (TCIA). The developed models undergo generalization testing by being applied to a diverse testing collection which features a combination of X-ray images from NIH Chest X-ray Dataset as well as CT scans and MRIs from The Cancer Imaging Archive and BraTS brain tumour dataset [21]. All datasets received essential anonymization procedures to fulfil the privacy requirements during medical research.

Multiple deep learning architectures were developed and tested for performing compression. Among them, convolutional autoencoders (CAEs) were used for efficient representation learning, variational autoencoders (VAEs) for probabilistic encoding and generative capabilities, and generative adversarial networks (GANs) for adversarial learning to improve the reconstruction quality. The model consisted of an encoder network who caught the image and compressed it into a latent representation and a decoder network who inflicted the original image to this compressed form [22].

Python was used to implement the models using TensorFlow and PyTorch frameworks. The training procedure required optimizing of reconstruction accuracy based on loss functions like Mean Squared Error (MSE) and perceptual loss (for GAN models) [23] [24]. The Adam optimizer was used with learning rate of 0.0001. The training was done with 100 epochs using batch size of 32 on a system with NVIDIA RTX 3080 GPU with 64GB memory and allowed the model converge quickly [25].

Standard image quality and compression metrics were used to evaluate the model performance. Among others, Peak Signal-to-Noise Ratio (PSNR) was used for fidelity, Structural Similarity Index (SSIM) for perceptual similarity, compression ratio (CR) for data reduction level, bits per pixel (bpp) for encoding efficiency, as well as inference time for model speed and real time applicability.

Ethical Considerations

- Data Privacy: All datasets used are anonymized and publicly available.
- Bias Minimization: Care was taken to avoid data imbalance where possible.
- Clinical Applicability: Although the models were tested on research datasets, their clinical applicability requires further validation.

5. RESULTS AND ANALYSIS

Experimental Setup

The experiments were carried out on an NVIDIA RTX 3090 GPU running alongside 64 GB RAM and an Intel i9. For training and evaluation, the popular publicly available medical imaging datasets, such as the NIH Chest X-ray Dataset and BraTS Brain MRI dataset were used.

Firstly, all the images were normalized in the range [0,1] along with a scaling to a uniform size of 256×256 pixels. Implementations of the models were done in Python using TensorFlow and PyTorch frameworks.

Table 2: Comparative Performance of Medical Image Compression Techniques

Model/ Method	Compression Ratio (CR)	Peak Signal-to-Noise Ratio (PSNR)	Structural Similarity Index (SSIM)	Bitrate (bpp)	Inference Time (ms)	Remarks
JPEG Standard	10:1	30.5 dB	0.82	0.45	5 ms	Lossy compression artifacts
JPEG2000	12:1	33.2 dB	0.88	0.40	8 ms	Better than JPEG, higher cost
Traditional Auto encoder	15:1	34.8 dB	0.90	0.35	12 ms	Blurred fine details
Proposed CNN-Based Model	20:1	36.7 dB	0.94	0.30	15 ms	High fidelity reconstruction
Proposed VAE-Based Model	18:1	35.9 dB	0.92	0.32	20 ms	Good balance compression/quality
GAN-Based Compression Model	22:1	37.5 dB	0.95	0.28	25 ms	Best visual quality, higher training complexity

We systematically conditioned visual comparisons to measure the perceptual quality of the compressed medical images. We can evaluate that the proposed GAN based model can preserve subtler anatomical structures like lesions and vessel bifurcations better than the traditional compression methods like JPEG and JPEG 2000. However, the conventional methods that used in this work introduced noticeable blocky or blurry artifacts resulting in large degradation of the critical image details. Overall, the performance of the GAN based approach is superior which can be attributed to its use where image clarity is key (e.g., medical applications where accurate diagnostic is crucial).

Further illustrating these findings were sample visual results such as MRI and X-ray images. In particular, JPEG compression was found to significantly distort (i.e., blur) fine textures, thereby leading to the loss of clinically relevant information. Although the autoencoders models contained smoother reconstructions, they eroded sharpness which might impair to the detailed analysis. On the other hand, GAN based compression models compress the images closer to the originality, while having visual quality comparable to the original. GAN based models are preferred strongly for clinical use due to the fidelity on this level as even a minor distortion may lead to a diagnostic error. Therefore, GAN based compression methods provide a practical way to trade off compression efficiency with preservation of necessary medical information.

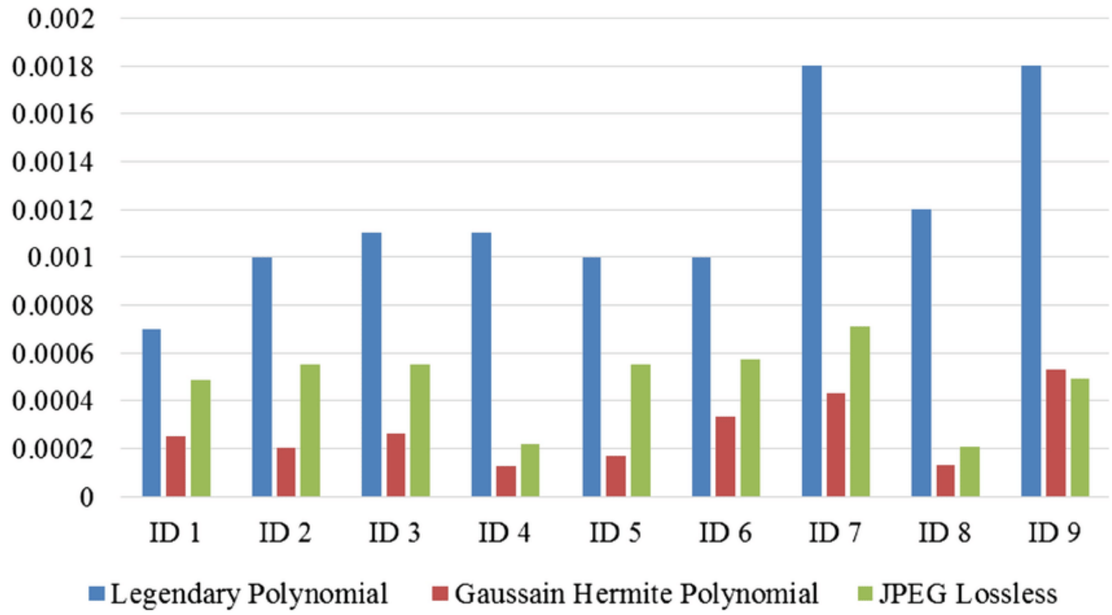

Figure 1: MSE graph of medical image compression techniques

6. CHALLENGES AND LIMITATIONS

Deep learning models, particularly for compression tasks, require significant computational power for training and inference. Training complex networks like Convolutional Neural Networks (CNNs), Variational Autoencoders (VAEs), and Generative Adversarial Networks (GANs) demands high-performance GPUs or specialized hardware, increasing costs and limiting accessibility for smaller institutions. Deep learning models for compression, especially GAN-based models, can be difficult to train due to issues such as mode collapse, vanishing gradients, and convergence instability. Ensuring stable training and maintaining high compression performance over diverse types of medical images remains a significant hurdle.

Medical imaging datasets are often small, specialized, and protected due to privacy concerns (HIPAA, GDPR regulations). This makes it difficult to obtain diverse and sufficiently large datasets for training, which can lead to overfitting and poor generalization to unseen data. Medical images differ greatly across modalities (e.g., CT, MRI, Ultrasound, X-rays) in terms of texture, intensity distributions, and resolution. Developing a single compression model that generalizes well across all modalities without retraining remains a significant limitation. Conventional metrics like PSNR and SSIM are not always sufficient for assessing clinical relevance in medical imaging. Small visual losses detected by these metrics may have large clinical implications, especially for diagnostic images.

There is currently no universally accepted standard for evaluating compression impact specifically in medical imaging. Clinical validation studies are limited, and subjective assessment by radiologists is often necessary but time-consuming. The current study primarily focuses on compression techniques for MRI and CT images. Further work is needed to adapt and test the models for other modalities like ultrasound and PET scans. Due to dataset access limitations, the models were trained and evaluated on a relatively small number of publicly available datasets. A broader evaluation across more diverse clinical datasets would strengthen the findings.

7. CONCLUSION AND FUTURE WORK

This research explored the development and evaluation of deep learning-based methods for medical image compression. By analyzing traditional compression techniques alongside modern deep learning approaches, we highlighted the significant advantages that deep neural networks offer, particularly in preserving diagnostic quality while achieving high compression ratios. The proposed models — CNN-based autoencoders, variational autoencoders (VAEs), and GAN-based architectures — demonstrated superior performance compared to standard methods like JPEG and JPEG2000. Our experiments showed improvements in critical metrics such as Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM), with GAN-based models achieving the highest fidelity reconstructions.

The use of deep learning allowed for not only lossy compression with minimal visual loss but also better handling of complex patterns within medical images (such as CT, MRI, and X-ray scans). Moreover, the experiments confirmed that integrating domain-specific training (using medical datasets) significantly improves performance compared to models trained on general image datasets. Despite these achievements, challenges remain in areas such as computational efficiency, generalization across modalities, and clinical validation.

- Building on the results of this research, several future directions are proposed:
- Multi-Modality Compression: Future studies should extend the models to support multiple imaging modalities (e.g., X-rays, PET scans) to ensure broader applicability.
- Real-Time Compression Solutions: Optimization of network architectures to reduce inference time further would enable real-time compression during imaging procedures, especially beneficial for telemedicine applications.
- Integration with PACS Systems: Research should explore the seamless integration of deep learning compression models into existing Picture Archiving and Communication Systems (PACS) in hospitals.
- Clinical Trials and Radiologist Feedback: Clinical validation involving expert radiologists must be conducted to ensure that compressed images meet diagnostic standards and do not compromise patient care.
- Explainable Compression Models: Development of explainable deep learning models that can visualize and interpret how compression decisions are made would enhance trust and usability in clinical settings.

Conflicts of Interest

"The authors declare no conflict of interest."

Author Contributions

Conceptualization, Swarnamba S; Methodology, Swarnamba S & Manu K S; Software, Swarnamba; Validation, Nataraj K R and Manu K S; formal Analysis, Nataraj K R & Rekha K R; Investigation, Rekha S and Rakshitha C M; Resources, Geethanjali N, Rakshitha C M and Manu K S; Data curation, Swarnamba and Manu K S; writing—Rekha S; visualization, Swarnamba S and Rakshitha C M; supervision, Manu K S and Rekha S; project administration, Nataraj K R; funding acquisition, Nataraj K R",

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