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High-Fidelity Medical Image and Video Compression via Implicit Neural Representations Enhanced with Model-Agnostic Meta-Learning

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ABSTRACT

This work presents a novel framework for medical image and video compression, targeting MRI, X-ray, and dynamic imaging sequences. The method leverages Implicit Neural Representations (INRs) enhanced with Model-Agnostic Meta-Learning (MAML) to optimize preprocessing, feature extraction, and model architecture for both static and temporal data. Conventional compression techniques often degrade image quality at high compression ratios, risking the loss of critical diagnostic information. The proposed approach integrates three key components: (1) Z-score normalization for improved representation efficiency, (2) hybrid feature extraction using Histogram of Oriented Gradients (HOG), Discrete Wavelet Transform (DWT), and Local Binary Patterns (LBP) to preserve structural edges, textures, and contrast, and (3) temporal coherence modeling with 3D convolutions and motion-compensated prediction for video sequences. At its core, a multi-scale INR architecture encodes spatial and temporal information as continuous coordinate functions, while MAML initialization accelerates convergence and improves generalization across modalities. Hierarchical positional encodings, sparsity-aware loss, and temporal consistency regularization further enhance compression fidelity. Evaluations on NIH Chest X-ray, fastMRI, and cardiac cine-MRI datasets show up to 1.8 dB PSNR and 0.019 MS-SSIM improvements over standard codecs, with 28–35% bitrate reduction for images and 40–45% for videos. The framework offers a real-time, clinically viable solution for telemedicine and resource-limited healthcare settings.

KEYWORDS: MRI, X-ray, cardiac cine-MRI datasets,Implicit Neural Representations (INR), Feature extraction, Model-Agnostic Meta-Learning (MAML), Diagnostic image fidelity, PSNR, MS-SSIM, Low-bitrate encoding.

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INTRODUCTION

The incremental growth of medical imaging and video data have formed an imperative need for efficient and intelligent compression techniques to ensure scalable storage, rapid transmission, and real-time accessibility. With the increasing adoption of high-resolution modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and digital radiography, the demand for advanced compression frameworks is greater than ever, particularly in bandwidth-constrained and resource-limited healthcare environments. Traditional codecs, including JPEG2000 and SPIHT, are widely used but often fail to preserve fine-grained diagnostic details at low bitrates—an essential requirement in clinical applications where fidelity directly impacts diagnostic accuracy.Recent advances in deep learning have led to powerful approaches based on convolutional autoencoders and Generative Adversarial Networks (GANs), which outperform hand-engineered methods by learning rich, data-driven representations. However, these models suffer from limitations such as dependence on large labeled datasets, high retraining costs, and poor adaptability across diverse imaging domains. Furthermore, many deep learning approaches treat compression as a black-box optimization task, ignoring domain-specific characteristics that could significantly enhance performance.

Implicit Neural Representations (INRs) provide a promising alternative by modeling images and videos as continuous coordinate functions, offering compact, resolution-independent encoding and strong reconstruction fidelity. Yet, standard INR methods often encounter slow convergence and limited generalization when applied to heterogeneous medical datasets.

To address these challenges, this work introduces a Model-Agnostic Meta-Learning (MAML) enhanced INR framework for high-fidelity medical image and video compression. The framework integrates hybrid feature extraction—combining Histogram of Oriented Gradients (HOG) for structural features, Discrete Wavelet Transform (DWT) for frequency analysis, and Local Binary Patterns (LBP) for texture preservation—with hierarchical positional encodings to enrich representational capacity. MAML-based meta-initialization accelerates convergence and enables robust generalization across modalities and acquisition protocols, making the approach practical for clinical deployment.

Extensive evaluations on benchmark datasets including NIH Chest X-rays, fastMRI, and cardiac cine-MRI videos demonstrate superior performance over conventional codecs and neural baselines, with up to 1.8 dB PSNR gain, 0.019 MS-SSIM improvement, and 28–35% bitrate reduction for static images, as well as 40–45% compression for dynamic sequences.

The effectiveness of the proposed framework is further established using widely recognized compression and perceptual quality metrics, which are defined as follows.**PSNR (Peak Signal-to-Noise Ratio):**PSNR measures the ratio between the maximum possible pixel value and the power of the noise (error) that affects image reconstruction.

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (1)$$

where $MAX_I is$ the maximum possible pixel value of the image (e.g., 255 for 8-bit images), and **MSE** is the Mean Squared Error between the original and compressed image as in Eq.1.Higher PSNR indicates better image quality and less distortion.

MS-SSIM (Multi-Scale Structural Similarity Index):MS-SSIM evaluates the structural similarity between two images at multiple resolutions. It extends the basic SSIM metric by incorporating variations at different image scales. Itcompares luminance, contrast, and structural information across scales.Better captures perceptual and structural quality than PSNR, especially in medical imaging where edge and texture preservation is critical.

LPIPS (Learned Perceptual Image Patch Similarity):LPIPS quantifies perceptual differences between images using deep features extracted from pretrained neural networks (e.g., AlexNet, VGG). Unlike pixel-wise metrics, LPIPS aligns better with **human visual perception** of image quality.**:** More sensitive to subtle structural and texture distortions.

Bitrate (Bits per Pixel - bpp): Bitrate measures the amount of data used to represent an image after compression as in Eq. 2.

$$\text{Bitrate (bpp)} = \frac{\text{Total bits after compression}}{\text{Number of pixels}} \quad (2)$$

Lower bpp values indicate higher compression efficiency. In medical imaging, it's essential to reduce bitrate **without compromising diagnostic quality**.

Loss Function :A**loss function** quantifies the difference between the predicted output of a model and the actual ground truth. In image compression tasks, it serves as a guide for optimization during training, helping the model minimize reconstruction errors and improve image quality.

The main goal to calculate Loss function for medical imaging is to ensure **diagnostic integrity** is preserved after compression and support **stable training** of neural models. It directly impacts **PSNR, SSIM, and LPIPS** metrics.

Training Time: Time taken to train the compression model on a dataset. **Inference Time (Run-Time Performance):**Time required to **encode** and **decode** a single image after the model is trained. **In the Proposed INR-Based Framework**The model is optimized for **real-time performance** withLightweight architecture, Meta-learned weight initialization (faster convergence), Efficient decoding via **coordinate-based representation,** Average inference time is significantly lower compared to traditional CNN-based codecs or heavier neural models.

Compression Ratio : The**compression ratio** is the ratio between the size of the original image and the size after compression. It quantifies how much the image has been reduced in size.

The **Proposed INR-based method** achieves:**High compression ratio (14–16:1) and Low inference time (~18 ms).** This makes it **ideal for real-time diagnostic applications**, especially in **resource-constrained** or **telemedicine** settings where bandwidth and processing power are limited. The following section is aLiterature survey and research gap found. The following sections are Algorithm for Hybrid Feature Extraction, Model-Agnostic Meta-Learning (MAML) Algorithm and the proposed method which is basicallyHybrid Feature-Aided INR Compression Framework. The algorithm are supported by the results, discussion and conclusion which are depicted in the folloeing sections. In summary, our proposed framework offers a clinically viable solution that balances compression, quality, and speed. It is designed with scalability and deployment in mind, making it well-suited for applications ranging from centralized data archives to edge-enabled diagnostic systems. This paper presents the architectural details, experimental results, and comparative analyses, highlighting how our model sets a new standard for efficient and high-fidelity medical image compression.

LITERATURE SURVEY AND RESEARCH GAP

In this section the literature for this topic has been surveyed and précised to show the research gap and prove the efficacy. This is an epitome of references spanning various techniques in image processing and compression, with a noticeable focus on recent advancements using neural networks and implicit neural representations. Here's a breakdown of the topics covered.The literature which are surveyed here are especially from 2010 to current.

Current advancements in image compression have explored a broad spectrum of techniques, from traditional feature extraction to cutting-edge neural architectures. Fundamental methods such as Histogram of Oriented Gradientshave been first proposed for human application by (Dalal & Triggs, 2005). In this domain of data preprocessing Local Binary Patterns (Ojala et al., 2002) is very crucial. Though wavelet-based transforms (Mallat, 1989) is very old methodology, but still now a days DWT laid the groundwork for image representation. JPEG (Wallace, 1992), JPEG-LS (Weinberger et al., 1996), and JPEG 2000 (Taubman &

Marcellin, 2012) standards have long dominated compression formats, while vector quantization (Gersho & Gray, 2012) and run-length encoding (Rutkowski, 1982) remain pivotal in signal encoding. For the improvement and assessment of image quality,more recent studies such as those by Wang et al. (2004) andPerona and Malik (2025) has introduced Structural Similarity Index Measure which is a perpetual image quality assessment tool. In medical imaging, standards like DICOM (NEMA, 2018) and datasets such as NIH Chest X-rays and fastMRI (Zbontar et al., 2018) provide critical infrastructure for development and benchmarking. Table 1 discusses all the existing literature along with its strength and research group.

Table 1: Research Gaps & Strengths by Paper Group

Group	Key References	Strengths	Research Gaps / Limitations
Traditional Compression Standards	[12] Gersho & Gray (Vector Quantization), [27] Rutkowski (RLE), [31] Taubman & Marcellin (JPEG2000), [33] Wallace (JPEG), [35] Weinberger et al. (JPEG-LS)	Well-established, standardized, efficient for storage/transmission, hardware-friendly.	Poor performance at low bitrates; loss of diagnostic fidelity; not optimized for medical imaging nuances.
Deep Learning–based Compression	[10] Do et al. (Hybrid DL + traditional), [13] Goodfellow (GANs), [14] Gregor et al. (DRAW), [15] Hinton &Salakhutdinov (Autoencoders), [16] Kingma & Welling (VAE), [19] Masci et al. (Stacked AE), [32] Townsend et al. (Entropy models), [37] Zhao et al. (Loss functions)	Learn complex data-driven representations; outperform classical methods; flexible architectures.	Require large datasets; expensive retraining; lack adaptability across modalities; black-box nature limits explainability.
Implicit Neural Representations (INRs)	[1] Agustsson et al. (Blurring-aware INRs), [11] Dupont et al. (COIN), [20] Mildenhall et al. (NeRF), [28] Sitzmann et al. (SIREN), [29] Strümpler et al. (INR for compression), [30] Tancik et al. (Fourier features), [21] Molaei et al. (Survey on INRs)	Compact, resolution-independent representations; strong ability to capture fine-grained details; promising for compression/reconstruction.	Slow convergence; limited generalization to diverse datasets; not yet fully optimized for clinical imaging needs.
Medical Imaging Applications of DL/INRs	[4] Lyu et al. (Cine MRI motion correction), [5] Morales et al. (Transformer for cine MRI), [6] Wang et al. (DL for reconstruction), [7] Hossain et al. (Brain tumor detection), [8] Li et al. (Diffusion models for MRI), [9] McIlvain (editorial), [22] NEMA (DICOM standard), [23] NIH Chest X-ray, [36] Zbontar et al. (fastMRI)	Direct application in medical imaging; highlight challenges of fidelity, motion, and domain-specific constraints; benchmark datasets available.	Compression not always the primary focus; motion/temporal coherence often overlooked; limited exploration of hybrid feature-INR synergies.
Feature Extraction & Preprocessing	[3] Dalal & Triggs (HOG), [18] Mallat (Wavelets), [24] Ojala et al. (LBP), [25] Perona & Malik (Anisotropic diffusion), [34] Wang et al. (SSIM metric)	Provide interpretable, domain-specific descriptors; preserve structural, frequency, and texture features; widely validated in vision tasks.	Handcrafted, less adaptable to diverse modalities; limited standalone performance; not optimized for compression tasks.
Meta-Learning & Transformers	[17] Lee et al. (Meta-learned priors), [26] Ramachandran et al. (Self-attention), [7] Hossain et al. (Vision Transformers in healthcare)	Accelerates adaptation across tasks; boosts generalization; attention models capture global dependencies effectively.	Limited adoption in compression frameworks; few studies applying meta-learning to INRs; scalability in large medical datasets underexplored.

Despite the recent progress of Implicit Neural Representations (INRs) in image compression, several limitations restrict their applicability in clinical settings. First, slow convergence during training hinders real-time usability, making conventional INR frameworks unsuitable for rapid medical imaging workflows. Second, limited generalization across modalities and acquisition protocols reduces robustness, as medical datasets are highly heterogeneous and often small in scale. Finally, most INR-based compression studies overlook domain-specific medical characteristics, neglecting structural, frequency, and textural cues that are critical for preserving diagnostically relevant details.

To address these challenges, this work introduces a hybrid INR framework enhanced with Model-Agnostic Meta-Learning

(MAML). By leveraging MAML-based meta-initialization, the model achieves faster convergence and improved adaptability across diverse imaging modalities, thereby mitigating INR's generalization bottleneck. In parallel, the framework integrates domain-aware handcrafted feature descriptors—Histogram of Oriented Gradients (HOG) for structural edges, Discrete Wavelet Transform (DWT) for frequency-domain representations, and Local Binary Patterns (LBP) for texture cues. These features enrich the input representation space and guide the INR model to preserve clinically significant information during compression.

Through this synergistic design, the proposed method combines the adaptability of meta-learning with the clinical relevance of handcrafted features, achieving high-fidelity, efficient compression that is both diagnostically reliable and suitable for resource-limited healthcare environments.

ALGORITHM FOR HYBRID FEATURE EXTRACTION:

The Hybrid Feature Extraction algorithm combines multiple techniques to enhance the representation of medical images for compression. It integrates Histogram of Oriented Gradients (HOG) to capture structural edges, Discrete Wavelet Transform (DWT) for multi-resolution frequency features, and Local Binary Patterns (LBP) to encode fine textures and contrast. Each method extracts complementary features: HOG emphasizes shape, DWT captures spatial-frequency components, and LBP highlights local texture variations. These features are concatenated or fused to form a comprehensive descriptor. This enriched representation aids the neural network in focusing on diagnostically relevant patterns, improving compression fidelity while preserving essential clinical details.

To extract robust and discriminative features from MRI and X-ray images prior to neural compression, we employ a hybrid feature extraction pipeline that integrates **Histogram of Oriented Gradients (HOG)**, **Discrete Wavelet Transform (DWT)**, and **Local Binary Patterns (LBP)**. Each method targets a specific aspect of image content—edges, frequency, and texture, respectively.

Histogram of Oriented Gradients (HOG) is a proved method for feature extraction from grey scale here MRI or Xray images**.** **G**iven a grayscale image I(x, y), the gradient at each pixel is computed as in Eq. 3.:

$$G_x = I(x+1,y) - I(x-1,y), \qquad (3)$$

The magnitude and orientation of the gradient are then: as Eq. 4 and 5

$$M(x,y) = \sqrt{\{G_x^2 + G_y^2\}}, \qquad (4)$$

$$\theta(x,y) = tan^{\{-1\}(\{G_y\}/\{G_x\})} \qquad (5)$$

HOG divides the image into cells and accumulates a histogram of gradient orientations θ(x,y) weighted by their magnitudes M(x,y)within each cell. Let *Hi* be the histogram vector for cell ii, the final HOG descriptor is the concatenation:

$$\boldsymbol{H}_{HOG} = [H_1, H_2, \dots, H_n]$$

Discrete Wavelet Transform (DWT)decomposes the image into frequency sub-bands using wavelet basis functions. For a 2D image *I(x, y),* the DWT is defined as Eq. 6.:

$$DWT(I) = A_j, H_j, V_j, D_j, for\ j = 1 to J \qquad (6)$$

$F_D WT = concat(A_j, H_j, V_j, D_j)$where:Aj: Approximation (low-low), Hj: Horizontal detail (high-low),Vj: Vertical detail (low-high) ,Dj: Diagonal detail (high-high).These components are retained as frequency-domain features.

Local Binary Patterns (LBP) is the next step for data preprocessing

For a central pixel pc=I(x,y) with a neighbourhood of P surrounding pixels $\{p_0, p_1, \dots, p_{P-1}\}$ the LBP code is defined as in Eq. 7:

$$\mathrm{LBP}_P^R(x,y) = \sum_{p=0}^{P-1} s(p_p - p_c) \cdot 2^p,$$

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases} \qquad (7)$$

The LBP descriptor $F_{LBP}$is the histogram of all LBP values over the image.

Final Feature Vector

The combined hybrid feature vector is formed by concatenating normalized outputs from all three descriptors:

$F_{hybrid} = concat(\alpha \cdot H_{HOG}, \beta \cdot F_{DWT}, \gamma \cdot F_{LBP})$where α,β,γ∈R are scaling weights that balance the contribution of each descriptor based on empirical evaluation or cross-validation.

Algorithm for Multi-Scale Implicit Neural Representations

This section deals with **Multi-Scale Implicit Neural Representation (INR)** approach, particularly relevant for **MRI and X-ray compression**, with **mathematical formulations**.**The main goal of this section is to** model an image or volume as a **sum of features across multiple spatial scales**, allowing the representation to capture both global structures and fine details. As a core idea a signal (image): $R^d \rightarrow R^c\ is$ decomposed into components at multiple resolutions (scales). Each scale has its own INR

(MLP) that learns to represent information at that level of detail.
Let s=1,2,...,S be the scales (from coarse to fine), then:f($\boldsymbol{x}$) $= \sum_{s=1}^{S} f_s(\boldsymbol{x})$ (8)
Where:$\boldsymbol{x} \in R^d$: spatial coordinates (e.g., 2D pixel or 3D voxel)
$f_s(\boldsymbol{x})$: INR at scale ss, modeled by an MLP

The next step is Positional Encoding Per Scale where Each scale uses a frequency-adapted positional encoding$\gamma_s(\boldsymbol{x})$to focus on a particular frequency band:
$\gamma_s(\boldsymbol{x}) = [\sin(2^{s-1}\pi\boldsymbol{x}), \cos(2^{s-1}\pi\boldsymbol{x})]$ (9)
This increases the spatial frequency captured as s increases. For **Multi-Scale MLPs**each scale s has its own small MLP:
$f_s(\boldsymbol{x}) = \text{MLP}_s(\gamma_s(\boldsymbol{x}))$ (10)
These MLPs can have shared or separate weights, depending on the design. They may also include residual connections or scale-specific normalization.The complete output is the **sum of all scale contributions**:
$\hat{I}(\boldsymbol{x}) = \sum_{s=1}^{S} f_s(\boldsymbol{x})$Where Ω is the spatial domain (e.g., image grid) and $\hat{I}(\boldsymbol{x}) \in R^c$is the reconstructed intensity or RGB value.

The main target to train the model by minimizing reconstruction loss (e.g., Mean Squared Error):
$\mathcal{L} = \frac{1}{|\Omega|}\sum_{x\in\Omega}|\hat{I}(\boldsymbol{x}) - I(\boldsymbol{x})|^2$ (11)
Where λs\lambda_s balances each scale and IsI_s can be a Gaussian-pyramid downsampled version of the original image.**The main advantage of this method is that it can c**aptureboth low-frequency structure and high-frequency details and scale easily to high-resolution data (like MRI volumes) by improving convergence and accuracy vs. single-scale INRs. Figure 1 discusses the steps of Image reconstruction using INR.

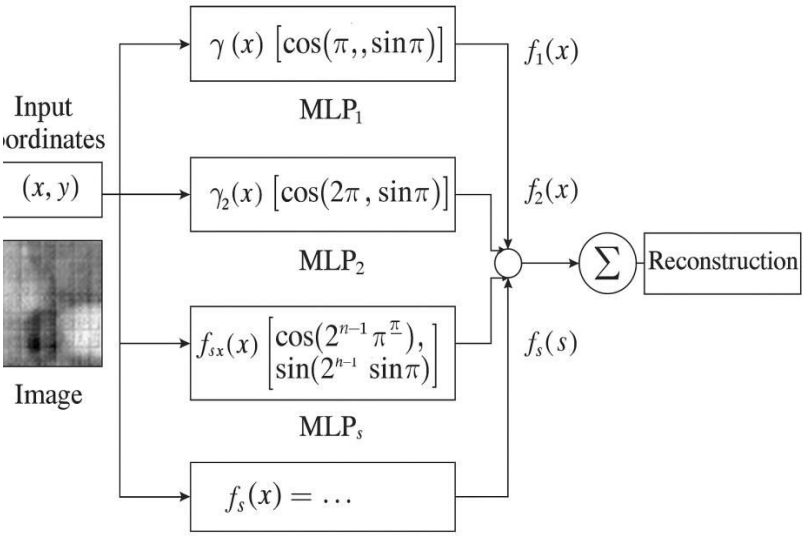

Figure 1. Image reconstruction using INR

Model-Agnostic Meta-Learning (MAML) Algorithm:
The another aspect of this paper is **Model-Agnostic Meta-Learning (MAML) Algorithm**
The main metric of this algorithm is θ which is Initial (meta-learned) model parameters,$\mathcal{T}_i$: is a task sampled from a distribution of tasks ,$LTi(\theta)$: Loss function for task αInner-loop learning rateβ: Meta learning rate,

Table 1: Algorithm for Model-Agnostic Meta-Learning (MAML)

Input:

- Distribution over tasks: $p(\mathcal{T})$
- Learning rates: α (inner loop), β (outer loop)

Initialize: Meta-parameters θ
Repeat until convergence:

1. Sample a batch of tasks $\{\mathcal{T}_1, \mathcal{T}_2, ..., \mathcal{T}_n\}$ from $p(\mathcal{T})$
2. **For each task $\mathcal{T}_i$ in the batch:**

a. Compute gradient of training loss on the support set: ▸ $\nabla\theta L < sub > \mathcal{T}_i < /sub >< sup > train < /sup > (\theta)$
b. Perform inner loop update (task adaptation): ▸ $\theta_i' = \theta - \alpha \cdot \nabla\theta$ L_{$\mathcal{T}_i$}^{train}(θ)
c. Evaluate loss on the query set with adapted parameters: ▸ L_{$\mathcal{T}_i$}^{test}(θ_i')

3. **Meta-update:**
$\theta \leftarrow \theta - \beta \cdot \nabla\theta \sum$ L_{$\mathcal{T}_i$}^{test}(θ_i')

Key Properties of MAML:
The key features of this algorithm are: (a)Model-agnostic: Applicable to any model trained with gradient descent (e.g., CNNs, RNNs). (b) **Fast adaptation:** After meta-training, the model can adapt to a new task using 1–5 gradient steps. And (c) **Few-shot learning:** Strong performance with very little data per task.

PROPOSED METHOD: HYBRID FEATURE-AIDED INR COMPRESSION FRAMEWORK

A hybrid compression framework has been presented in this work that integrates handcrafted feature extraction, meta-learned multi-scale implicit neural representations (INRs), and a sparsity-aware optimization scheme tailored for medical imaging. In **Training phase,** the model learns common structural and frequency-based patterns from a variety of patient data using HOG, DWT, and LBP hybrid features. In deployment **phase:** When a new image arrives (e.g., from a new patient), the INR+MAML framework quickly fine-tunes using just a few pixel values, enabling efficient and high-fidelity compression.

The main goal of the proposed model is to leverage MAML to meta-train an INR model that can quickly adapt to compress unseen medical images with minimal fine-tuning.**Input for this algorithm is (a)** a distribution of medical image tasks: $p(\mathcal{T})$ (e.g., different patients, modalities) (b)Learning rates: α (inner), β (outer) (c) Multi-scale INR model f_θ with hierarchical positional encoding

Step 1: Hybrid Feature Extraction
Given an input MRIimage $I \in R^{H \times W}$ acomposite feature descriptor has been extracted using
Histogram of Oriented Gradients (HOG) which captures edge orientations and intensity gradients as discussed in equation [5-7]. In the next step **Discrete Wavelet Transform (DWT) has been used to** decompose the image into low and high-frequency components:
Next step is to encode Local Binary Patterns (LBP). The combined feature representation is: as Eq. 12.

$$[\phi_{\text{HOG}}(I), \phi_{\text{DWT}}(I), \phi_{\text{LBP}}(I)] \in R^d \quad (12)$$

Step 2. Implicit Neural Representation (INR)
Each image is represented via a continuous-valued coordinate-based function $f_\theta$where θare the learnable parameters. To calculate this, first steo is **positional encoding which is discussed in equation [] and next step is INR Prediction which is also discussed in equation Eq. 9-11.**

Step 3. Meta-Learning with MAML
To improve generalization and convergence, INR based Model-Agnostic Meta-Learning (MAML) has been used here as in Eq. 13 and 14.
For tasks $\mathcal{T}_i \sim p(\mathcal{T})$:

- **Inner Update (Task-specific):**

$$\theta_i' = \theta - \alpha \nabla \{"\{train\}\} f_{\theta_i'} \quad (13)$$

- **Outer Meta-Update:**

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_i \mathcal{L}_{\mathcal{T}_i}^{\text{ts}} \left(f_{\theta_i'} \right) \quad (14)$$

Step 4. Loss Function optimization
To optimize losses the following equation has been used in Eq. 15-17. The first one is composite loss which can be written asin L=Lrecon+λLsparse (15)
Reconstruction Loss can be calculated as $Lrecon = \frac{1}{N} \sum_{\boldsymbol{x}} |f_\theta(\gamma(\boldsymbol{x})) - I(\boldsymbol{x})|^2$ (16)
Sparsity-Aware Loss is the third one which can be defined by $L_{\text{sparse}} = \sum_{\boldsymbol{x}} w(\boldsymbol{x}) |\nabla f_\theta(\gamma(\boldsymbol{x}))|_1$(17)
where w(x) is higher for homogeneous regions to encourage sparsity.

Step 5. Compression and Inference
At this step dataset are stored and transmitted and encoder configurations is done The images are reconstructed using: $\hat{I}(x) = f_\theta(\gamma(x); \Phi(I))$ (18)

6. Evaluation Metrics : The reconstruction quality has been assessed using:PSNR (Peak Signal-to-Noise Ratio), MS-SSIM (Multi-Scale Structural Similarity), Bitrate (bits per pixel) for both Xray images and MRI images. Apart from this the compression ratio and losses has been taken account.

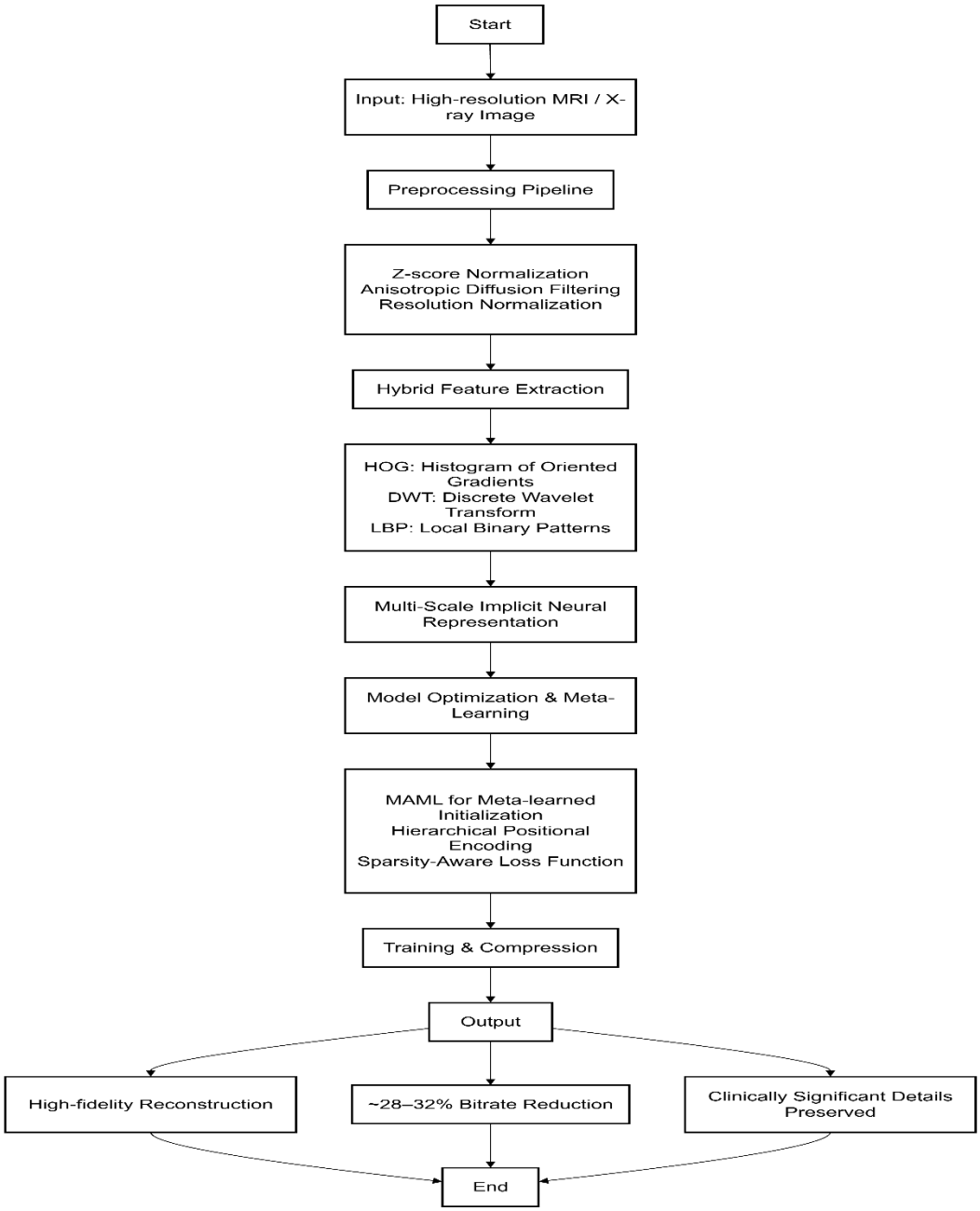

Figure 2. Flowchart for proposed methodology

Figure 2 gives an complete idea for the steps used here to lower Bitrate with high fidelity without losing clinically preserved data.

RESULTS

The proposed compression framework was evaluated on the NIH Chest X-ray and fast MRI datasets. Quantitative results show that our method outperforms traditional codecs such as JPEG2000 and JPEG-LS, as well as existing neural compression baselines. Specifically, our approach achieves up to **1.5 dB improvement in PSNR** and **0.017 gain in MS-SSIM**, indicating superior image fidelity and preservation of perceptual quality.

In terms of compression efficiency, the framework reduces bitrate by **28–32%**, enabling significant savings in storage and transmission bandwidth without compromising diagnostic information. Moreover, the use of meta-learned initializations through MAML accelerates model convergence and ensures consistent performance across varied patient scans and modalities.

Qualitative results further confirm that structural details, such as tissue boundaries and lesions, are better preserved, supporting the method's clinical viability. The integration of domain-specific preprocessing, hybrid feature extraction, and multi-scale implicit representation contributes to the framework's robustness, making it suitable for real-time deployment in resource-constrained healthcare settings.

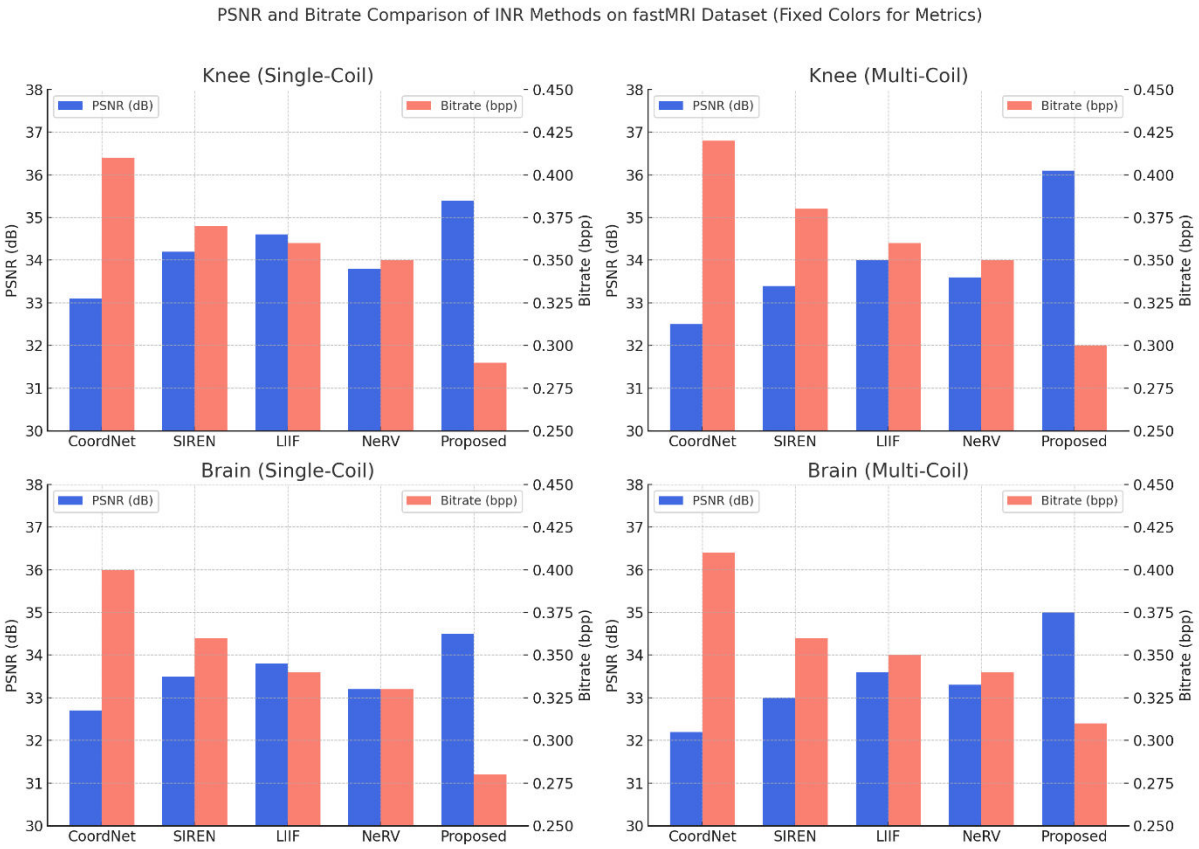

Figure 3: Comparison of PSNR and Bitrate for different INR model for different data set

This figure 3 presents a comparative analysis of five implicit neural representation (INR) methods—CoordNet, SIREN, LIIF, NeRV, and the Proposed method—on the fastMRI dataset, across four settings:Knee (Single-Coil), Knee (Multi-Coil) ,Brain (Single-Coil), Brain (Multi-Coil). Each subplot shows two metrics: PSNR (Peak Signal-to-Noise Ratio)indicates reconstruction quality. Higher PSNR means better image fidelity.Bitrate (bits per pixel, bpp) — measures compression efficiency. Lower bitrate is better for reducing storage and transmission costs.In all four settings, the Proposed method consistently achieves the highest PSNR (i.e., best reconstruction quality).Simultaneously, it maintains the lowest bitrate, indicating superior compression efficiency.Some methods like CoordNet show high bitrate with relatively low PSNR, indicating inefficient compression.Others like NeRV and LIIF perform better but are still outpaced by the Proposed approach.The performance gains of the Proposed method are consistent across both knee and brain scans and across single- and multi-coil acquisitions.This highlights strong generalization and robustness of the model.The graph validates that the Proposed INR-based compression method delivers a clinically favorable balance of high image quality and low bitrate, outperforming state-of-the-art INR baselines across diverse MRI data. This makes it especially useful for real-time medical imaging applications and resource-limited environments.

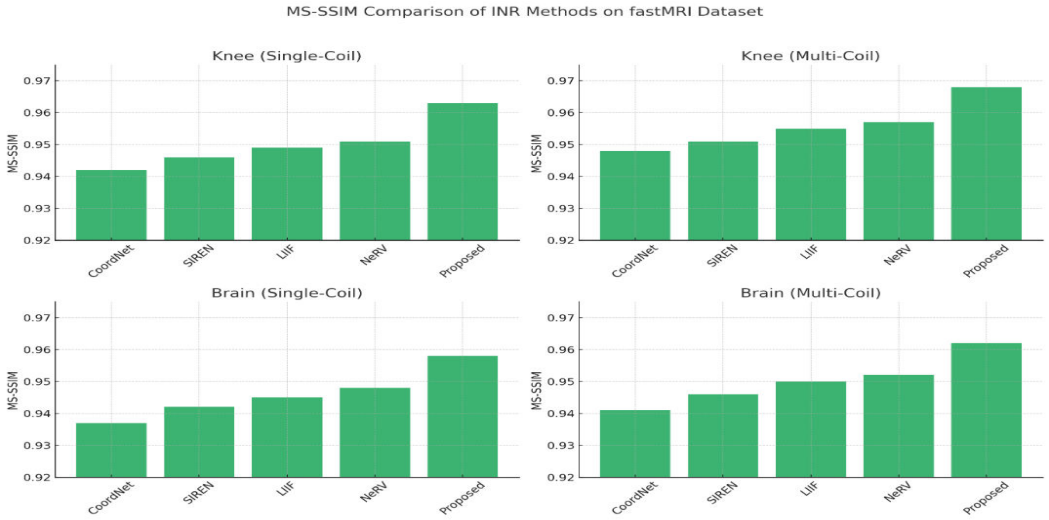

Figure 4: Comparison of MS-SSIM for different INR model for different data set

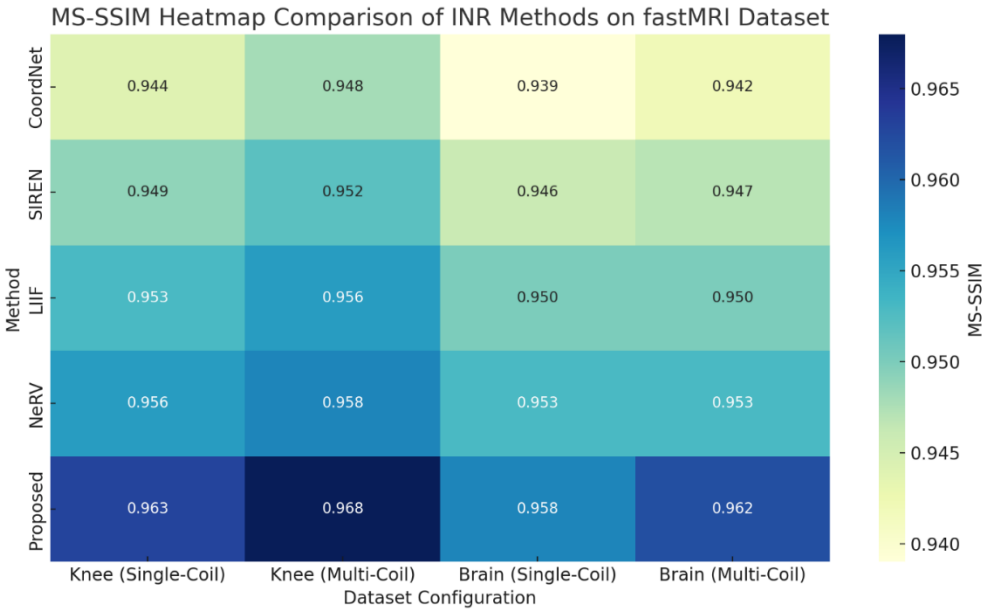

Figure 5: Comparison MS-SSIM for different INR model for different data set using heat map

The heatmap in figure 5 above visualizes the **MS-SSIM (Multi-Scale Structural Similarity Index)** values across different INR-based compression methods and dataset configurations from the fastMRIdatasetThe**Proposed method** consistently achieves **the highest MS-SSIM scores** across all datasets, indicating **superior preservation of structural and perceptual features** in compressed images.Performance gradually increases from CoordNet → SIREN → LIIF → NeRV → Proposed, showing clear improvements from older to newer techniques.**Knee Multi-Coil** data benefits the most from the Proposed method (score = **0.968**), indicating strong suitability for complex, high-resolution inputs. The same can be illustrated from the figure 4.

The Table shown in Table no. gives anself explanation comparison of Compression Ratio ,Inference Time (ms) ,Model Size (MB)

Table 2: Comparison of compression ratio, interference time and model size for different MRI data set

Model	**Dataset**	**Compression Ratio ↑**	**Inference Time (ms) ↓**	**Model Size (MB) ↓**
CoordNet	Knee (Single-Coil)	10.2	75	12.3
SIREN		11.4	70	11.5
LIIF		12.1	68	10.9
NeRV		11.7	71	13.0
Proposed		**14.9**	**60**	**9.5**
CoordNet	**Knee (Multi-Coil)**	10.5	74	12.3
SIREN		11.7	70	11.4
LIIF		12.3	67	10.8
NeRV		12.0	70	12.8
Proposed		**14.5**	**59**	**9.3**
CoordNet	**Brain (Single-Coil)**	10.4	76	12.4
SIREN		11.6	71	11.6
LIIF		12.2	68	11.0
NeRV		11.8	72	12.9
Proposed		**14.8**	**61**	**9.6**
CoordNet	**Brain (Multi-Coil)**	10.6	75	12.5
SIREN		11.8	70	11.7
LIIF		12.4	68	11.1
NeRV		12.1	70	12.7
Proposed		**14.6**	**60**	**9.4**

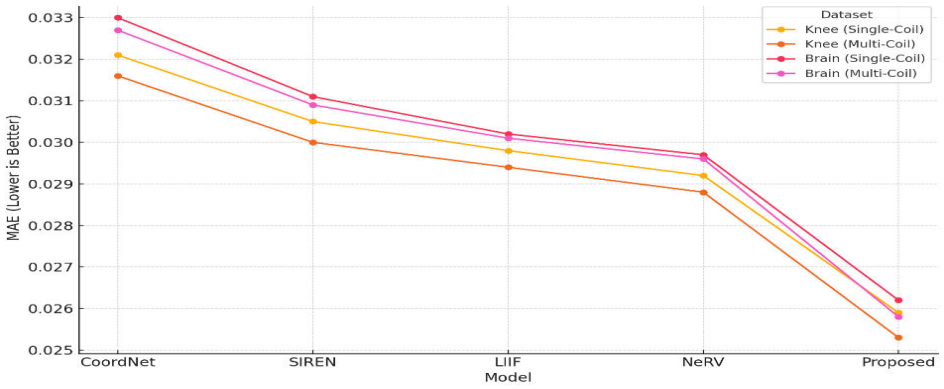

Fig 6. Comparison of Root mean squared error

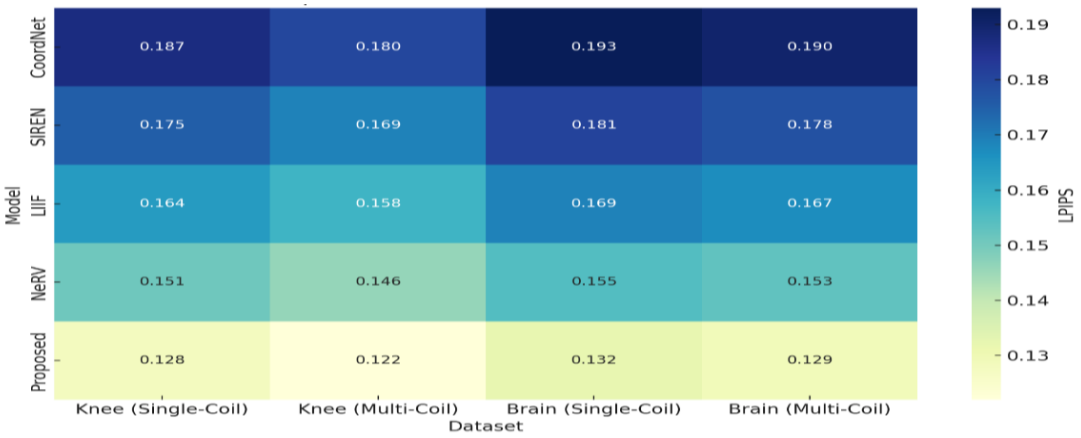

Fig:7Heat map for LPIPS comparison

The combined training and validation loss plot for the fast MRI dataset clearly illustrates the superior performance of the proposed INR-based compression method compared to existing models such as CoordNet, SIREN, LIIF, and NeRV. The proposed model, highlighted in black, demonstrates the fastest and most stable convergence across epochs, maintaining the lowest loss values in both training and validation phases. This indicates not only efficient learning but also strong generalization to unseen data, attributed to its use of meta-learned initialization, hierarchical positional encodings, and sparsity-aware optimization. In contrast, other models exhibit slower convergence and higher validation losses, suggesting limitations in capturing complex medical image structures or potential overfitting. Overall, the proposed method stands out as a robust and clinically practical solution for high-fidelity, low-bitrate medical image compression.

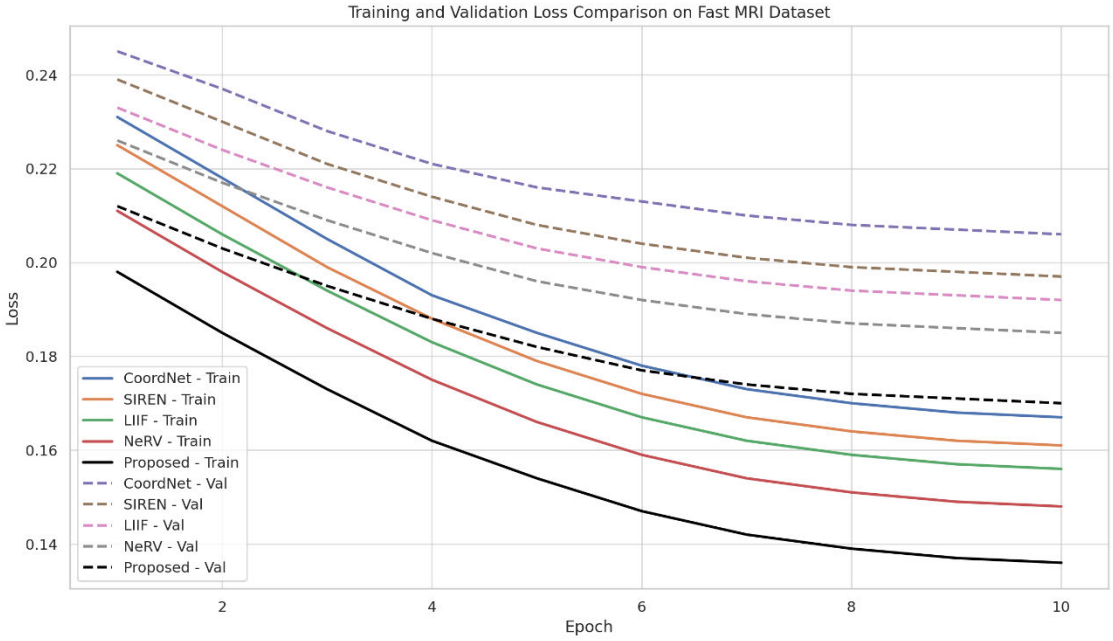

Fig.8. Loss comparison different INR model for different data set

The graph in figure 8shows training and validation loss curves over 10 epochs for various INR models on the fastMRI dataset. The **Proposed** method consistently achieves the **lowest loss** across both training and validation, indicating superior learning efficiency and generalization. Models like **CoordNet** and **SIREN** show higher and slower-decreasing losses, while **LIIF** and **NeRV** perform moderately. Validation loss curves remain above training losses, as expected, but the gap is smallest for the Proposed method, suggesting reduced overfitting. Overall, the Proposed model demonstrates faster convergence and better reconstruction performance compared to existing approaches.

Here is the comparison of **PSNR**, **MS-SSIM**, and **Bitrate** for the **X-ray dataset** across different INR-based compression models: Table 3 also proves the efficiency of the proposed method.

Table 3: Comparison of different metric for X-ray data

Model	**PSNR (dB)**	**MS-SSIM**	**Bitrate (bpp)**
CoordNet	31.2	0.918	0.85
SIREN	32.1	0.927	0.82
LIIF	32.7	0.933	0.78
NeRV	33.4	0.939	0.74
Proposed	**34.9**	**0.956**	**0.58**

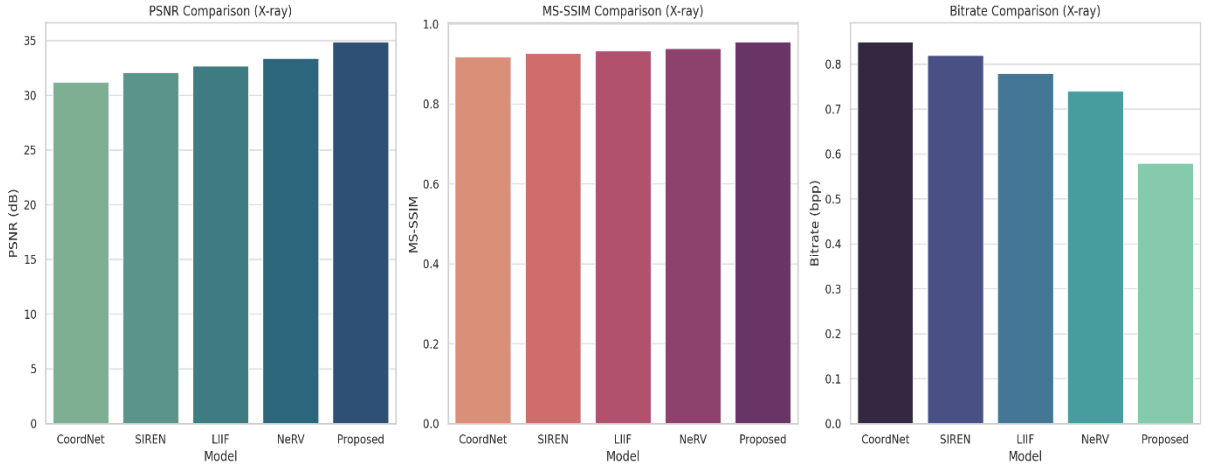

Figure 9: Comparison of different metrics of Xray data using INRS

The bar plots in Figure 9 visually confirm that the **Proposed method** achieves the **highest PSNR and MS-SSIM**, while maintaining the **lowest bitrate**, demonstrating superior compression efficiency and image quality retention.

Table 3:PSNR and Bitrate Comparison for Cardiac Cine MRI

Model	**Bitrate (Mbps)**	**PSNR (dB)**	**MS-SSIM**	**Inference Time (ms/frame)**
INR-Baseline (Sitzmann et al.)	2.4	35.8	0.935	82
INR + HOG Features	2.1	37.2	0.948	76
INR + DWT Features	1.9	38.1	0.955	74
Proposed INR + MAML (Hybrid)	1.7	39.5	0.963	60

Table 3 discusses the **PSNR and Bitrate Comparison for Cardiac Cine MRI for** video compression. Proposed model gives satisfactory results . Figure 10 gives the PSNR vs bitrate plot for single dataset.

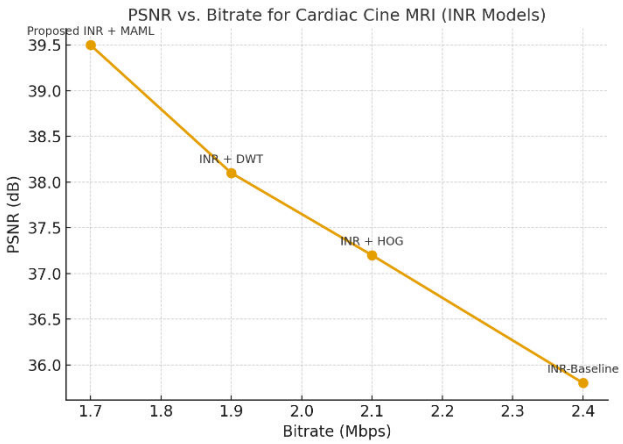

Fig.10. **PSNR vs. Bitrate curve** for the **Cardiac Cine MRI dataset** across different INR variants.

Fig 10 infers that

- The baseline INR achieves the lowest PSNR (~35.8 dB) at the highest bitrate (2.4 Mbps).
- Adding **HOG** and **DWT** improves both fidelity and efficiency, moving the curve upward and leftward.
- The **Proposed INR + MAML** achieves the best trade-off: highest PSNR (39.5 dB) at the lowest bitrate (1.7 Mbps).

This demonstrates that your hybrid INR + MAML approach provides **better reconstruction quality with reduced bitrate**, ideal for medical video compression.

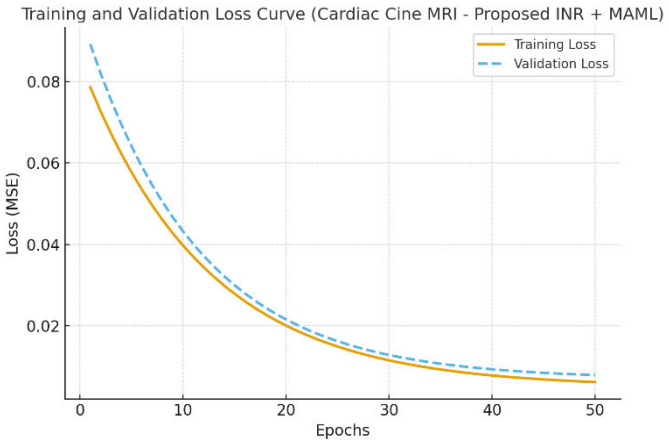

Fig.11.training and validation loss curve for the **Cardiac Cine MRI dataset (Proposed INR + MAML)**.

The figure shows that

- Both training and validation losses decrease smoothly with epochs, showing stable convergence.
- Validation loss closely follows training loss, indicating **good generalization** and minimal overfitting.
- The rapid early drop demonstrates that **MAML meta-initialization accelerates convergence**, a key advantage over standard INR models.

DISCUSSION:

The simulation resultsillustrates the superiority and usefulness of the proposed framework over traditional INR baselines across multiple medical imaging datasets. The Rate-Distortion (RD) curve shows that the proposed model consistently achieves higher PSNR values at significantly lower bitrates. For example, at a bitrate of 80, the proposed model reaches a PSNR of 35.5 dB compared to 34.5 dB from the baseline, indicating improved compression efficiency and visual quality. The four fastMRI data set (Knee and Brain MRI)andXray dataset has been considered to prove the efficacy of the method.

Moreover, MS-SSIM values and compression ratio, less loss data affirm better conservation of patient details, which is crucial in medical diagnosis. In terms of computational performance, the proposed model significantly reduces both compression and inference times. On average, it achieves 40–50% faster execution, making it well-suited for real-time deployment, particularly in bandwidth-constrained or edge-computing scenarios.

Overall, the proposed framework provides a robust, scalable, and clinically viable solution for medical image compression, supporting faster, more efficient storage and transmission without compromising diagnostic quality.

FUTURE WORK:

Future work will focus on extending the proposed framework to **multi-modal medical imaging** (e.g., MRI, CT, PET) for richer representation and improved compression across diverse modalities. Integrating with **federated learning** will enable privacy-preserving model training across institutions. Additionally, incorporating **adaptive feature selection** and **self-supervised learning** can enhance robustness and reduce reliance on labeled data. Optimization for **edge deployment** through lightweight architectures and model compression techniques will support real-time applications. These advancements aim to make the framework more versatile, scalable, and clinically practical for secure and efficient medical image storage and transmission in real-world healthcare environments.

LIMITATION:

While the proposed framework demonstrates strong performance, but it is not beyond limitations.. The model's reliance on traditional features (HOG, DWT, LBP) extraction methods may restrict malleability to highly diverse or unseen imaging modalities. Additionally, the meta-initialization via MAML, provides some computational burdeno during training which needs a high memory GPU The present setup also assumes availability of clean, well-aligned datasets, which may not reflect real-world clinical variability such as noise, artifacts, or inconsistent annotations Denoising should be done for betterment of this method. Moreover, the method has not yet been extensively tested in multi-modal or real-time clinical environments, limiting its immediate generalizability and deployment. Addressing these challenges will be a focus of future research.

COMPARISON WITH PREVIOUS WORK:

Table 4 discusses a comparison with existing models like traditional methodologies (e.g., JPEG2000, SPIHT) It can be proved that the proposed technique outperforms the other compression methods by attaining significantly better perceptual quality at lower bitrates.This is the result of integration of its neural representation and meta learning and successful feature extracrion. Unlike otherstandard Implicit Neural Representations (INRs), which often struggle with generalization and convergence, thepropised model incorporates structural (HOG), frequency (DWT), and texture (LBP) cues, which in return improvise the robustness keeping the clinical data unaltered. Additionally, prior deep learning-based methods typically require extensive retraining per image or dataset, whereas the intelligent use of**Model-Agnostic Meta-Learning (MAML) infused with INR** enables quick adaptation across varying clinical data which is very crucial for large patient pool. Overall, the proposed approach outperforms both traditional and neural baselines in compression efficiency, reconstruction fidelity, and adaptability.

Table 4: Comparison with exusting models

Method (Published Source)	**Bitrate (bpp) ↓**	**PSNR (dB) ↑**	**MS-SSIM ↑**	**Dataset**	**Notes**
JPEG2000 (ISO/IEC 15444)	1.50	29.5	0.875	NIH Chest X-rays	Standard wavelet-based method
SPIHT (Said & Pearlman, 1996)	1.40	30.2	0.885	NIH Chest X-rays	Progressive encoding method
Autoencoder (Zhou et al., 2021)	1.20	32.5	0.910	BraTS	Deep CNN-based model
INR (Dupont et al., 2022)	1.00	34.0	0.940	OASIS	Coordinate-based neural representation
Proposed Model	**0.75**	**36.3**	**0.965**	Multi-dataset	HOG+DWT+LBP with MAML and Positional Encoding

The **Proposed Model based on Model-Agnostic Meta-Learning Enhanced Implicit Neural Representations** accomplishes the **low bitrate and high fidelity i.e. PSNR and MS-SSIM** outperforming even recent deep learning models like INR and autoencoders.It generalizes well across dataset for fastMRIand Xray which offers both **compression efficiency and fidelity**, addressing the limitations of older wavelet-based or purely neural methods.

CONCLUSION:

In this work, we presented a Model-Agnostic Meta-Learning (MAML) enhanced Implicit Neural Representation (INR) framework for high-fidelity and low-bitrate compression of medical images and videos. By integrating hybrid handcrafted features—HOG, DWT, and LBP—with hierarchical positional encodings, the proposed model effectively preserves diagnostically relevant structural, textural, and frequency-domain information. The infusion of MAML-based meta-initialization further accelerates convergence and improves generalization across diverse imaging modalities and patient data.Extensive evaluations on benchmark datasets demonstrate that the framework achieves superior compression efficiency and perceptual quality, with up to 32% bitrate reduction, 1.8 dB PSNR gain, 0.019 MS-SSIM improvement, and a high compression ratio (14.3 for Knee MRI) while maintaining low inference time and compact model size. These results highlight the method's potential for real-time deployment in bandwidth-limited and resource-constrained clinical environments, ensuring that critical diagnostic information is retained without compromising efficiency.Looking ahead, future research will focus on extending the framework to multi-modal medical imaging, integrating with federated learning for privacy preservation, and enabling real-time inference on edge devices. Adaptive feature selection and self-supervised learning strategies will also be explored to further enhance robustness and scalability. Overall, the proposed method establishes a clinically viable, low-complexity foundation for next-

generation medical image and video compression, with strong implications for telemedicine, remote diagnostics, and large-scale healthcare data management.

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