Enhancing Scientific Image Prediction and Compression through AI Model Fine-Tuning

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Background & Motivation

Large-scale scientific facilities such as SPring-8[1] generate massive volumes of X-ray Computed Tomography (XCT) data. Efficient storage and transmission of these high-resolution, high-bit-depth images is a critical challenge.

Recent AI-based compression methods, such as TEZip[2], show strong performance but are:

- Limited to non-time-evolutionary data
- Trained on non-scientific image datasets

As a result, reconstruction errors remain structured, leading to high residual entropy and limiting the compression ratio.

| For scientific image compression, improving reconstruction accuracy is important not only for visual quality, but also for reducing residual entropy.

Key Idea

We propose an AI-based scientific image compression framework where:

| Fine-tuning a super-resolution model on scientific data improves reconstruction accuracy in a compression-aware manner, resulting in more compressible residuals.

Proposed Method

Pipeline Overview

1. Downsample the original high-resolution XCT image
2. Reconstruct the image using a super-resolution model
3. Compute the delta image (pixel-wise difference)
4. Losslessly compress both:
   - Downsampled image
   - Delta image (using FFV1 codec[3])

| Since delta image compressibility strongly depends on reconstruction accuracy, improving the reconstruction model is key.

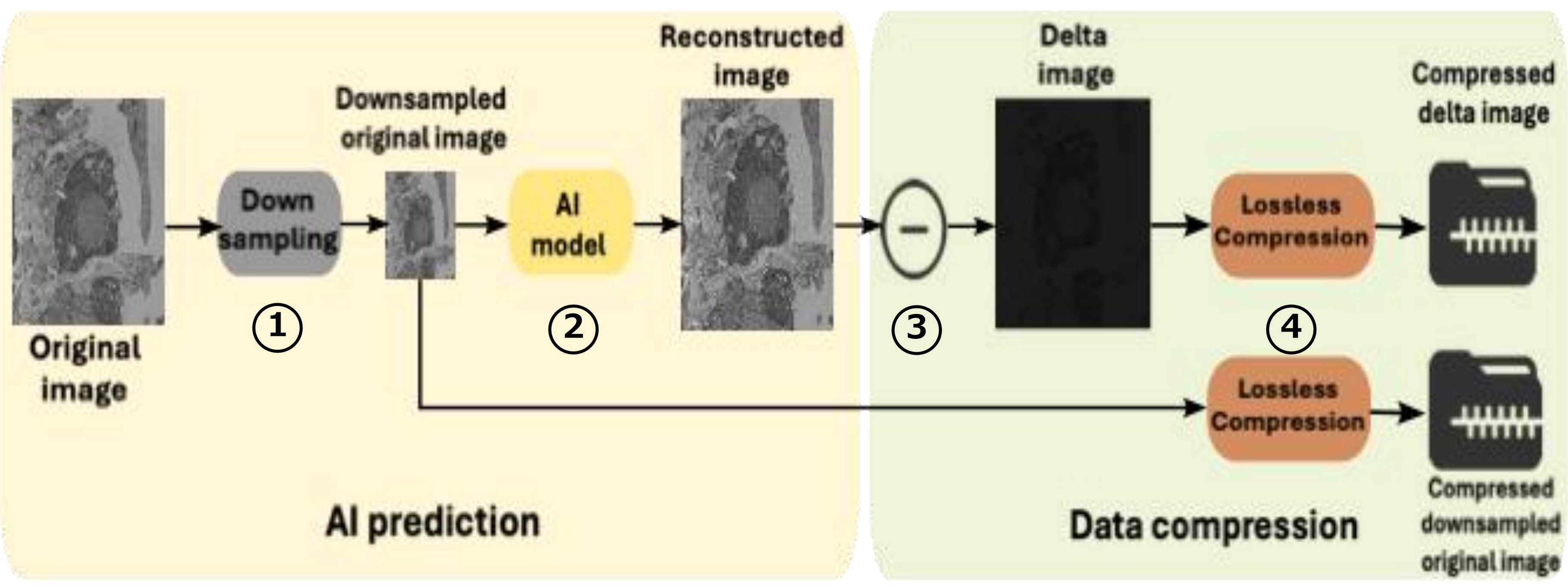

Figure 1. The proposed AI-based compression pipeline

Model Fine-Tuning

- AI model: SwinIR[4] ($\times 4$ Super-Resolution)
  - Transformer-based image restoration model
  - Uses shifted window self-attention to capture both local textures and long-range structures
- Dataset: XCT-2K (904 scientific XCT images, 16-bit grayscale)
  - 700 training pairs
  - Remaining images for testing
- Training:
  - 50, 100, 150, 200, 250, 300 epochs
  - Batch size: 4
  - Loss: Charbonnier loss
  - Optimizer: Adam
  - GPU: NVIDIA A100

Evaluation Metrics

To assess both reconstruction quality and compression performance, we evaluate:

- PSNR(Peak Signal-to-Noise Ratio)
- Shannon Entropy of Delta Image
- Compression Ratio
  - Delta image only (CR Δ)
  - Overall compression (CR Overall)

Result

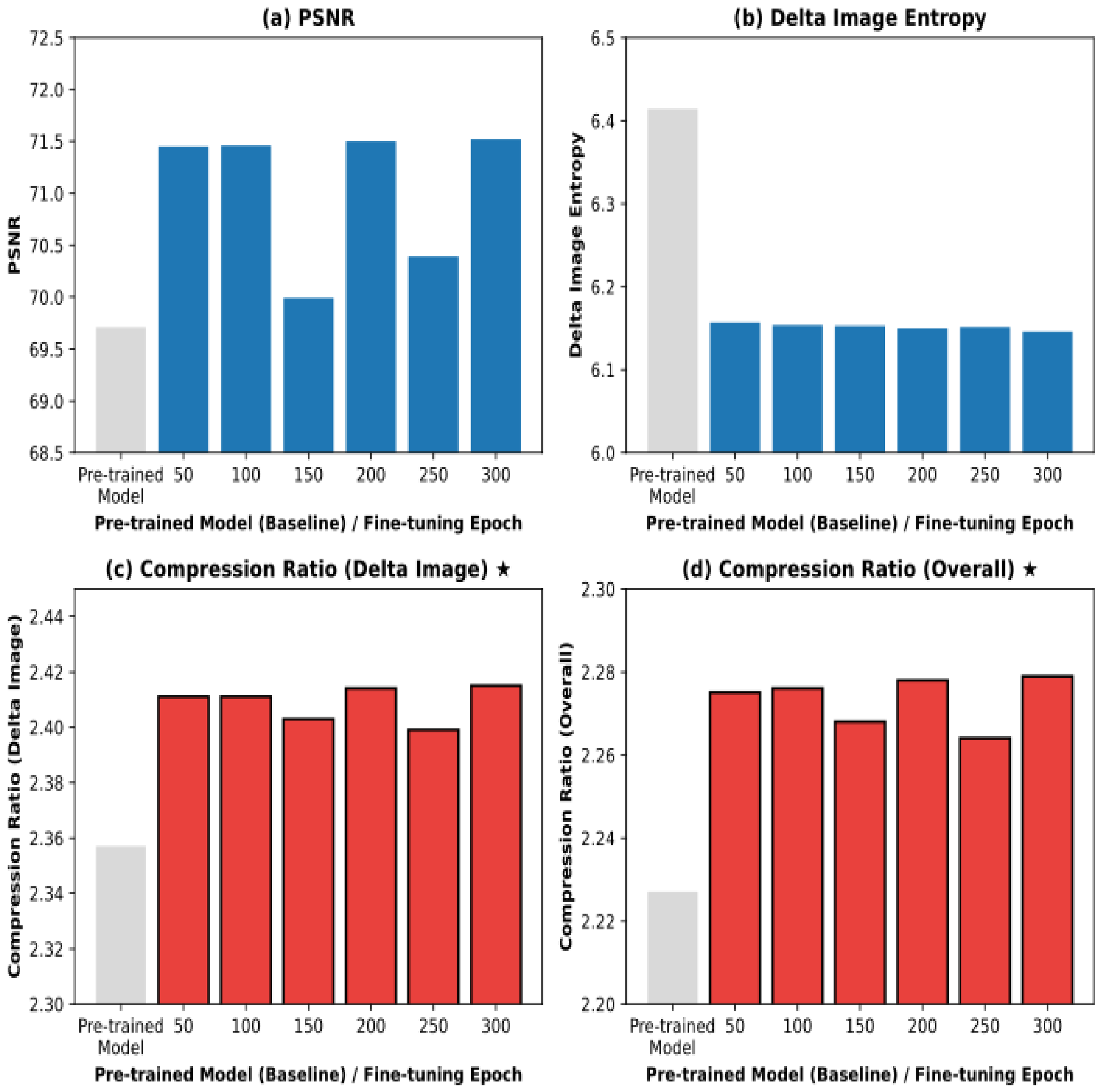

Figure 2. Comparison between the pre-trained SwinIR model and fine-tuned models trained for different numbers of fine-tuning epochs.

Key Observations

- PSNR improved by ~1.8 dB, indicating better pixel-level reconstruction
- Delta image entropy consistently decreased (from 6.414 to 6.146), improving lossless compressibility.
- The compression ratio increased by 0.058 (2.46%) for the delta image and by 0.052 (2.34%) for the overall pipeline.

Conclusions and Future Work

In this study, we proposed an AI-based scientific image compression approach and fine-tuned the pre-trained model on scientific XCT data, achieving improvements in reconstruction accuracy and compression ratio compared to the pre-trained model.

Future work will focus on a more efficient encoding method for the delta image to further enhance the compression.

Acknowledgement

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References

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