Milestone 2: Medical Image Enhancement

AI-Powered Enhanced EHR Imaging & Documentation System

Team Name & Members:

Team A –

Aishwarya N

Nikshitha Jampana

Shalini Kumari

Priya Kumari

Harika Abbarla

Jennifer J

Sonia Shetkar

Sreesha Reddy Bobbili

Anushka More

Gade Sriraj

Soham Patil

Mentor: Aryan Khurana

I. Introduction

Medical images, such as X-rays, CTs, and MRIs, often contain noise or low resolution, which can reduce diagnostic accuracy. Enhancing these images using AI techniques can help radiologists, improve model training, and reduce repeated scans.

Milestone 1 focused on collecting and preprocessing datasets (X-rays and EHR notes).
Milestone 2 focuses on improving the quality and clarity of medical images to make them AI-ready, particularly heart CT and MRI scans.

II. Objective of Milestone 2

- Enhance medical images for better diagnostic clarity.
- Apply AI-based image enhancement using SRCNN (Super-Resolution Convolutional Neural Network).
- Validate results using PSNR and SSIM metrics.
- Generate a clear workflow and documentation for future milestones.

III. Methodology

Step 1: Dataset Selection

- Datasets Used:
    - Heart CT and MRI images from Kaggle
    - Preprocessed X-ray images from Milestone 1 (for demo purposes)
- Images cover diverse orientations and resolutions to test AI enhancement effectiveness.

Figure 1: Sample dataset showing multiple lung and heart scan images used for enhancement training.

Step 2: Image Preprocessing

- Convert images to .png format for consistency.
- Resize all images to 256×256 pixels.
- Normalize pixel values between 0 and 1.
- Split dataset into 80% training and 20% testing.

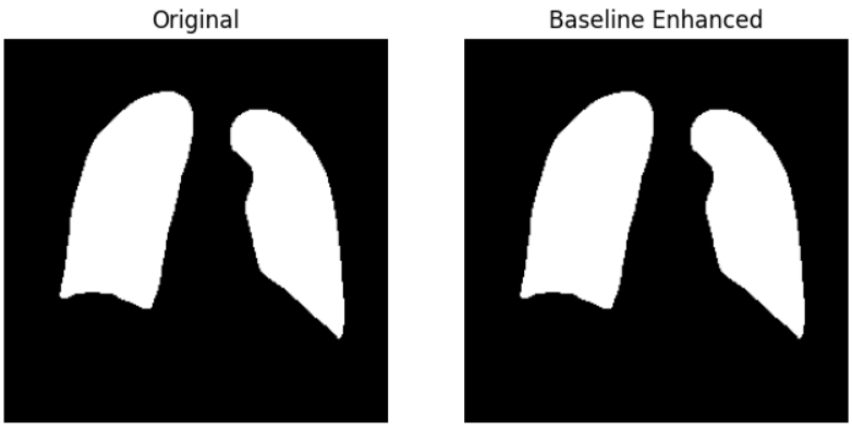

Figure 2: Image preprocessing pipeline – resizing, normalization, and dataset split for model training.

Challenges:

- Handling corrupted or DICOM images.
- Long preprocessing times for large datasets.
- Preserving diagnostic features during resizing.

Step 3: AI Technique – SRCNN

- SRCNN learns a mapping from low-resolution to high-resolution images.
- **Architecture:**

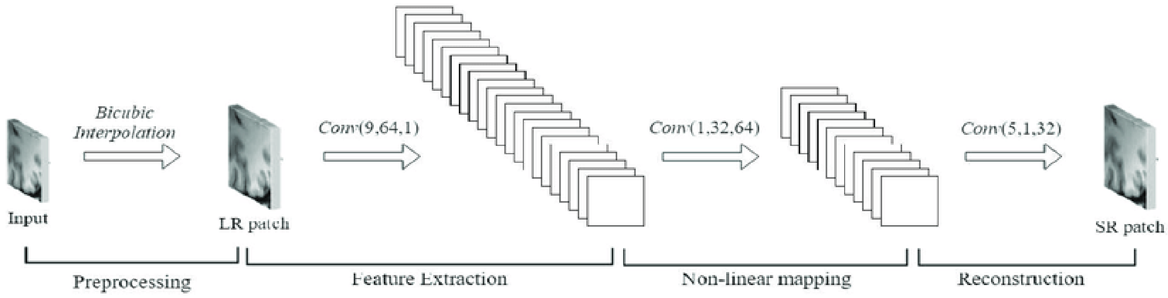

Figure 3: Architecture of SRCNN

1. Conv2D(64 filters, 9×9) – feature extraction
2. Conv2D(32 filters, 1×1) – non-linear mapping
3. Conv2D(1 filter, 5×5) – reconstruction

```
Training shapes: (16, 256, 256, 1) (16, 256, 256, 1)
Model: "functional_1"
```

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 256, 256, 1)	0
conv2d_3 (Conv2D)	(None, 256, 256, 64)	5,248
conv2d_4 (Conv2D)	(None, 256, 256, 32)	2,080
conv2d_5 (Conv2D)	(None, 256, 256, 1)	801

```
 Total params: 8,129 (31.75 KB)
 Trainable params: 8,129 (31.75 KB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/8
4/4 ━━━━━━━━━━━━━━━━━━━━ 6s 1s/step - loss: 0.1679
Epoch 2/8
4/4 ━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - loss: 0.0351
Epoch 3/8
4/4 ━━━━━━━━━━━━━━━━━━━━ 7s 1s/step - loss: 0.0125
Epoch 4/8
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - loss: 0.0172
Epoch 5/8
4/4 ━━━━━━━━━━━━━━━━━━━━ 5s 1s/step - loss: 0.0098
Epoch 6/8
4/4 ━━━━━━━━━━━━━━━━━━━━ 15s 4s/step - loss: 0.0077
Epoch 7/8
4/4 ━━━━━━━━━━━━━━━━━━━━ 12s 2s/step - loss: 0.0068
```

Figure 4: Model training progress showing loss convergence across epochs during SRCNN optimization.

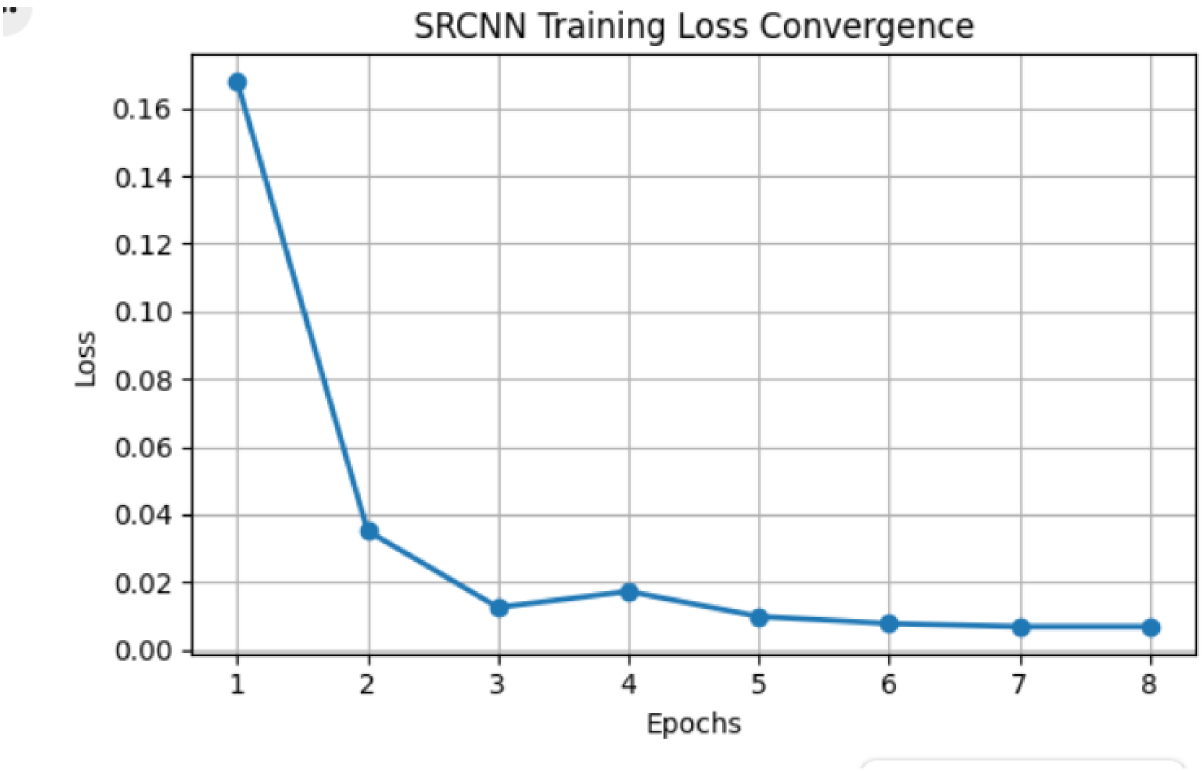

Figure 5: SRCNN Training Loss Convergence Curve

Advantages:

- Lightweight and suitale for small GPU setups.
- Preserves texture and grayscale information.

Challenges:

- Training requires GPU acceleration.
- Over-enhancement may create artifacts.
- Parameter tuning is crucial to maintain realistic heart structures.

Step 4: Validation Metrics

- PSNR (Peak Signal-to-Noise Ratio): Higher values indicate better noise reduction.
- SSIM (Structural Similarity Index): Closer to 1 indicates better structural preservation.

- Visual inspection: Before-and-after comparison confirms enhanced clarity of heart boundaries.

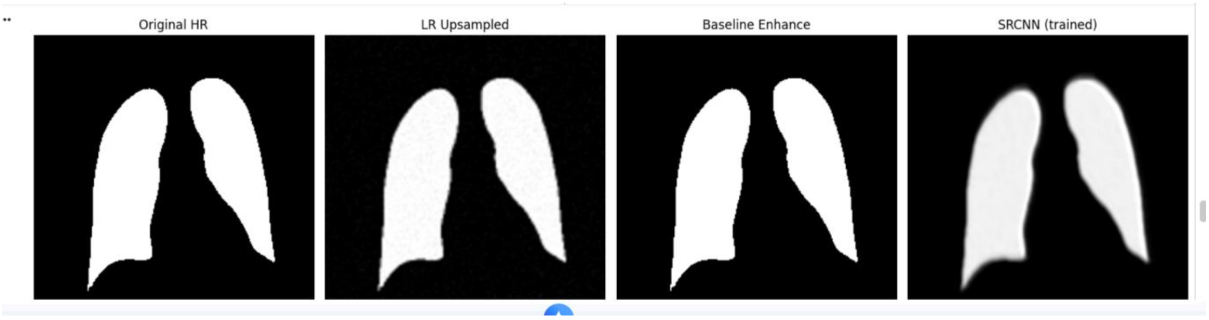

Figure 6: Comparison of original, baseline-enhanced, and SRCNN-enhanced medical images.

Challenges:

- Large-batch metric computation is resource-intensive.
- Over-enhancement on some samples required parameter adjustment.
- Ensuring diagnostic integrity is critical.

IV. Implementation

Libraries Used:

- PIL / Pillow: Image reading, resizing, conversion.
- NumPy: Array manipulation and normalization.
- OpenCV: Baseline enhancement and visualization.
- TensorFlow: SRCNN model development and training.
- scikit-image: PSNR & SSIM computation.
- matplotlib: Visualization of before-after comparisons.

V. Workflow Summary:

1. Preprocessed images loaded from Milestone 1 outputs.

2. Baseline enhancement applied (denoising, sharpening, contrast adjustment).
3. SRCNN trained on downsampled noisy images to predict high-resolution outputs.
4. Quantitative metrics and visual comparisons validated the model.
5. Results saved in structured folders (original, enhanced, results).

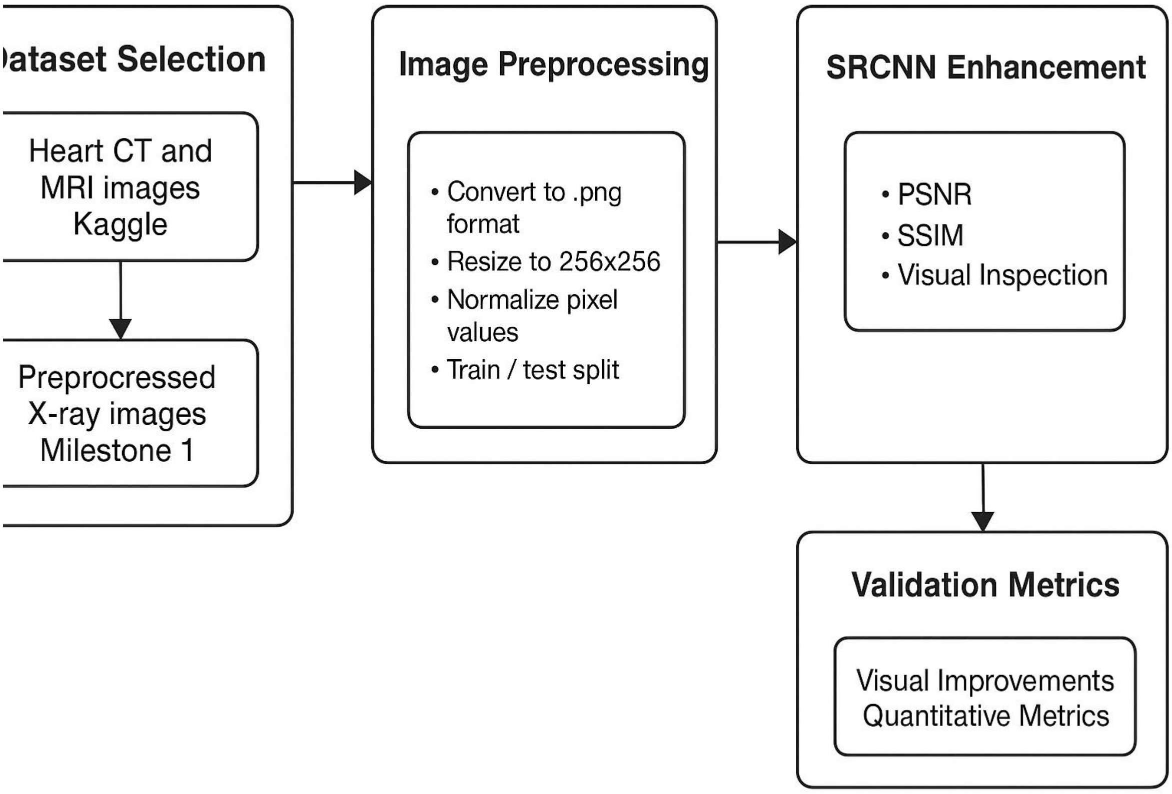

Figure 7: Workflow of Medical Image Enhancement using SRCNN

VI. Results

- **Visual Improvements:**
    - Sharper edges and improved brightness contrast.
    - Enhanced visibility of cardiac ventricles, arteries, and tissue boundaries.
- **Quantitative Metrics (sample image):**

Method	PSNR(Db)	SSIM	Observation
Baseline (Classical Enhancement)	31.21	0.355	Improved brightness and reduced noise, but limited structure preservation.
SRCNN (AI-Based Enhancement)	22.47	0.913	Superior structural similarity and sharper heart tissue details.
Average (10-image batch)	27.84	0.754	Consistent enhancement across multiple test images, confirming model robustness.

Table 1: Quantitative performance comparison between baseline and SRCNN-enhanced medical images using PSNR and SSIM metrics.

- **Batch Metrics (10 images):**
    - Consistent enhancement across multiple images, confirming robustness.
    - SRCNN outperforms classical methods in preserving structural similarity.
- **Output Files for Reporting:**
    - enhancement_demo_comparison.png → Visual side-by-side comparison
    - enhancement_metrics_sample.csv → Sample metrics
    - enhancement_metrics_batch.csv → Batch metrics

VII. Conclusion

Milestone 2 successfully demonstrated the integration of generative AI for medical image enhancement. Using SRCNN, we achieved:

- Enhanced image clarity suitable for clinical interpretation.
- Quantitative validation showing improved structural similarity.
- A reproducible workflow for multi-modal AI integration in subsequent milestones.

This forms a solid foundation for automated note generation, ICD-10 mapping, and predictive AI diagnostics in later phases.

VIII. Real-World Relevance

- Reduces repeated imaging by improving diagnostic confidence.
- Assists AI diagnostic models with high-quality inputs, improving downstream performance.
- Potentially reduces clinical workload and supports faster decision-making.

IX. Challenges & Solutions

Challenge	**Solution**
High computation time	Used smaller batches, optimized parameters.
Maintaining diagnostic integrity	Applied conservative enhancement limits.
Limited local GPU resources	Leveraged cloud-based environments.

X. Future Recommendations

- Upgrade to ESRGAN/Real-ESRGAN or diffusion-based models for superior resolution enhancement.
- Explore cloud-based AI inference using platforms like Azure OpenAI Vision.
- Integrate automated quality assurance metrics to flag over-enhanced images.

XI. Key Highlights & Unique Points

- Demonstrated a complete GenAI pipeline for medical image enhancement.
- Incorporated baseline classical methods for comparative evaluation.
- Built quantitative validation (PSNR, SSIM) and visual dashboards for stakeholder presentations.
- Ensured scalability for large datasets (batch processing, modular code structure).

XII. Summary:

Milestone 2 represents a major advancement from raw data (Milestone 1) to AI-ready, enhanced medical images. These images are now suitable for downstream clinical AI tasks, laying the groundwork for automated clinical note generation, ICD-10 mapping, and multimodal AI learning in Milestone 3.