Milestone 2 Documentation

Project Title: AI-Powered-Enhanced EHR Imaging & Documentation System
Team Name & Members: Team A

- Samriddhi Tiwary
- Hima Anjuri
- Pravalika
- Rajeswari
- Dhanasree
- Sushmasri
- Shazfa
- Shobith Reddy
- Gokula prasath

Course / Semester / Instructor Name: Aryan Khurana
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Introduction

In healthcare, doctors and radiologists spend a significant amount of time on documentation, image processing, and analysis — tasks that can often be automated using Artificial Intelligence.
Our project, *AI-Powered Enhanced EHR Imaging & Documentation System*, aims to integrate **Generative AI** for improving efficiency, accuracy, and consistency in clinical workflows.

While **Milestone 1** focused on **collecting and cleaning medical datasets**, **Milestone 2** was about **enhancing medical images** to make them AI-ready and diagnostically clearer.
In this phase, we focused on **Heart CT and MRI scans** to demonstrate how AI-based enhancement techniques can improve medical image clarity, ultimately supporting better diagnosis and model performance.

🎯 Objective of Milestone 2

The main objective of Milestone 2 was to:

- Enhance the **quality and clarity** of heart CT and MRI images for better diagnostic understanding.
- Apply **AI-based image enhancement techniques** such as **SRCNN (Super-Resolution Convolutional Neural Network)**.
- Validate improvements through both **visual comparison** and **quantitative metrics** like PSNR and SSIM.
- Document the process, results, and real-world challenges clearly for future integration in later milestones.

⚙️ Methodology

Step 1: Choosing the Dataset

- **Dataset Used:** [Heart CT and MRI Dataset – Kaggle]

- This dataset provides a collection of **Cardiac CT and MRI images**, which are crucial for heart diagnosis.
- The images are diverse in orientation and resolution, allowing us to test enhancement models effectively.
- We selected this dataset because it represents **real-world cardiac imaging data** and supports multimodal analysis — essential for AI-driven healthcare applications.

Step 2: Preprocessing the Images

Before enhancement, images were preprocessed to ensure uniformity and quality.

Steps Performed:

- Converted all images into **.png** format for consistent quality and compatibility.
- Resized all images to **256×256 pixels** for uniform input to the model.
- **Normalized pixel values** between 0 and 1 to stabilize model training and reduce bias.
- Split the dataset into **training (80%)** and **testing (20%)** sets for validation.

Challenges Faced:

- Some images were corrupted or in DICOM format, requiring conversion tools.

- Large image size led to longer preprocessing times on local systems.
- Ensuring that no diagnostic features were lost during resizing was critical.

Step 3: Picking a Technique – SRCNN

We selected **SRCNN (Super-Resolution Convolutional Neural Network)** for image enhancement because it's one of the most effective deep learning models for improving image resolution and clarity.

Why SRCNN:

- It learns to **map low-resolution images to high-resolution ones**, improving visual detail.
- Lightweight architecture suitable for limited hardware environments.
- Proven performance on medical and grayscale images.

Challenges Faced:

- Training SRCNN from scratch requires GPU acceleration and time.
- Over-enhancement can create artifacts, so balancing clarity and authenticity was crucial.
- Parameter tuning was needed to maintain natural texture in heart MRI and CT images.

Step 4: Validating the Improvement

After enhancement, we validated the quality using both **quantitative metrics** and **visual comparison**.

Validation Metrics Used:

- **PSNR (Peak Signal-to-Noise Ratio):** Measures how much clearer the enhanced image is compared to the original.
- **SSIM (Structural Similarity Index):** Assesses how similar the enhanced image is to the original in terms of structure and texture.
- **Visual Comparison:** Before-and-after images showed sharper edges, reduced blur, and more defined heart boundaries.

Challenges Faced:

- Calculating PSNR/SSIM for large batches was computationally expensive.
- Slight over-enhancement in a few images required parameter fine-tuning.
- Ensuring that enhancement did not alter diagnostic patterns was a key concern.

💻 Implementation

Libraries Used:

- **PIL (Pillow):** For reading, resizing, and converting images.

- **NumPy:** For pixel normalization and array manipulation.
- **OpenCV (cv2):** For basic image enhancement and visualization.
- **TensorFlow / PyTorch:** For implementing and experimenting with SRCNN models.
- **scikit-image:** For PSNR and SSIM calculation.
- **matplotlib:** For displaying before-and-after comparisons.

Implementation Summary:

- Images were read and preprocessed using **PIL** and **OpenCV**.
- SRCNN was applied to the dataset to generate higher-quality outputs.
- Validation metrics were computed to measure performance.
- All outputs were saved in structured folders (/original, /enhanced, /results).

📊 Results

- Enhanced images showed **clearer edges and improved brightness contrast**, making the heart structures more visible.
- **PSNR values** improved significantly, indicating reduced noise.

- **SSIM scores** confirmed that structure and texture were preserved.
- Visually, radiographic clarity improved — especially around ventricular and arterial boundaries.

□ Conclusion

Milestone 2 demonstrated how **AI-based image enhancement** can make medical imaging more interpretable and diagnostically useful.
Using **SRCNN**, we successfully enhanced Heart CT and MRI images, validated the improvements quantitatively, and documented the entire workflow.

Real-World Relevance

In clinical settings, image noise or low resolution often delays diagnosis. AI-driven enhancement tools like SRCNN can:

- Improve diagnostic accuracy in radiology.
- Reduce the need for repeated scans (saving time and cost).
- Assist in training AI diagnostic models using cleaner data.

Challenge	Solution
High computation time	Used smaller batches and optimized model parameters.
Maintaining diagnostic integrity	Applied conservative enhancement limits
Limited local GPU resources	Used cloud-based environments for experimentation.

🌍 Why We Chose This Focus

We selected this milestone because **image quality directly impacts AI performance and clinical outcomes**. Enhancing medical images is a foundational step before applying classification, segmentation, or report generation models.
By improving image clarity, we create a more reliable pipeline for the next milestones, ensuring that **data fed into AI models is optimized, accurate, and meaningful**.

▯ Summary

Milestone 2 marked a major step in our project's progression — from collecting data (Milestone 1) to improving it (Milestone 2).
We applied real AI techniques, tackled real challenges, and

produced results that are both technically strong and practically relevant.

Our documentation, methods, and validation form a robust base for the **next phase — automating clinical note generation and ICD-10 mapping**, where these enhanced images can contribute to multi-modal AI learning.