SEEJPH Volume XXV,S2, 2024, ISSN: 2197-5248;Posted:05-12-2024

ADVANCING MRI SUPER-RESOLUTION: AN INNOVATIVE DEEP LEARNING APPROACH FOR ENHANCED RADIOLOGICAL STRUCTURE SUPER-RESOLUTION

Ashwini P. Navghane[1], Ketki Kshirsagar[2], Rajendra Talware[3]

[1]*ashwini.navghane@viit.ac.in*
[2]*ketki.kshirsagar@viit.ac.in*
[3]*rajendra.talware@viit.ac.in*

KEYWORDS

ABSTRACT

This study focuses on the application of deep learning algorithms to super-resolution in medical MRI images to improve radiological structures, which has, in the recent times become extremely important to the diagnostics. The methodology for the purpose involved preprocessing and augmentation MRI images, to improve model generalization. Multiple algorithms which use differing flows to enhance an image, were selected for evaluation. These included: 1) Bicubic Interpolation, 2) SRCNN, 3) EDSR, and 4) ESRGAN. The models were assessed using key performance metrics like Peak Signal-to-Noise-Ratio (PSNR), Mean Squared Error (MSE) and Structural Similarity Index Measure (SSIM). ESRGAN was found to have highest PSNR (33.75 dB) and SSIM (0.98), while one of the lowest MSE (82.44). Conclusively, ESRGAN showed a superior and structural integrity and perceptual quality over all other models on medical images. It was demonstrated that ESRGAN is able to better restore fine details and textures than the state of the art, especially for medical imaging where precision is critical. The qualitative visual assessments also confirmed that ESRGAN dominates in the super-resolution image quality, as its reconstructed images matched high resolution and very precisely maintained critical radiological features. As this study concludes, ESRGAN is the most effective for super-resolution of MRI images, and has great potential for improving the diagnostic capabilities in medical imaging.

I. INTRODUCTION

1.1: Overview

The domain of medical image processing, particularly in the context of radiology, has seen significant advancements with the integration of deep learning techniques. One of the major challenges in this field is improving the resolution of medical images, such as MRI scans, without compromising critical structural details [12]. With the recent increasing interest in super resolution (SR) techniques as a way to improve the resolution of low-res medical images, there has been a significant amount of effort put into developing these techniques. The algorithms it uses include particularly complex algorithms, such as deep learning models, to reconstruct high resolution images from low resolution scan images [13-15]. These techniques could increase image clarity and help in better diagnoses — especially in radiological analysis when fine structures such as tissues, organs and lesions require very precise imagery for correct diagnostics. A sample low-res image of an MRI scan, and a super-resolution enhanced image set is shown in fig 1.1.

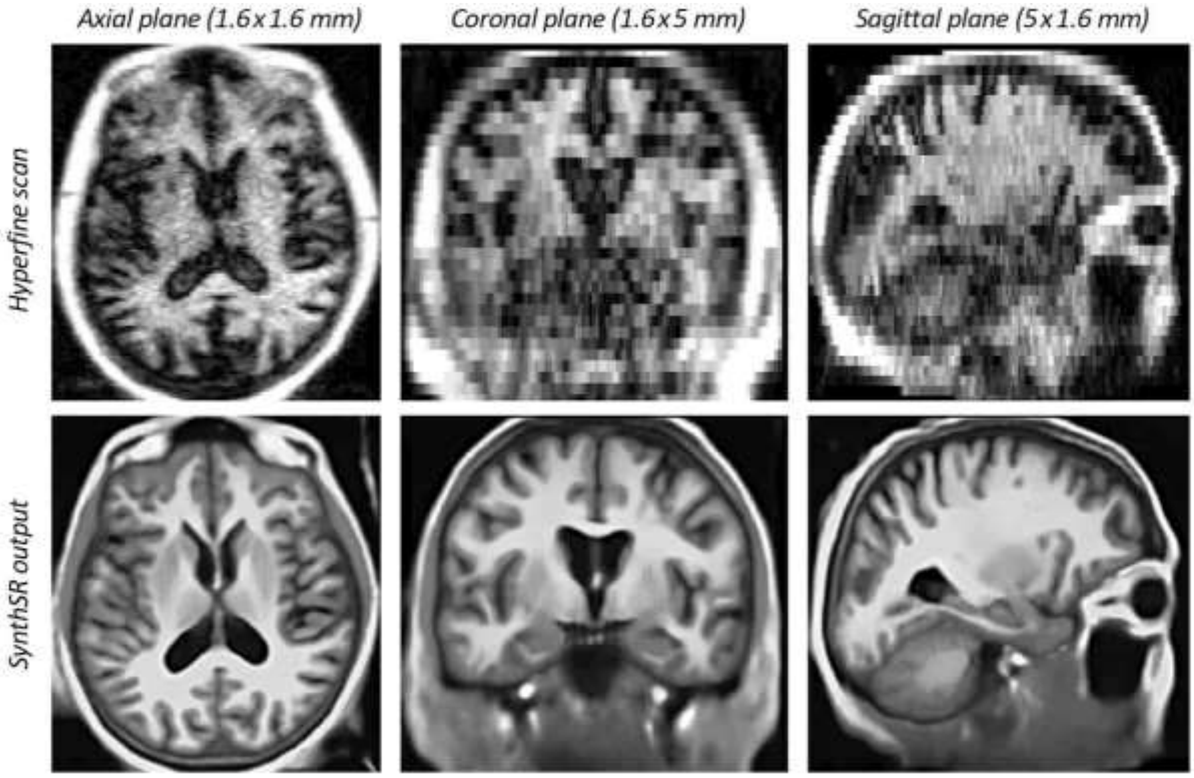


Fig 1.1: AI Regenerated vs High resolution MRI images

As the need for high quality imaging in healthcare continues to grow, the opportunity to improve medical image resolution through deep learning is a transformative opportunity in the diagnostic process.

1.2: Aim and Objectives

In this work, we evaluate the effectiveness of multiple deep learning models in reconstructing MRI image to high resolution via super resolution techniques. Ten MRI videos were picked out for testing, and the performances of various super resolution models were evaluated with PSNR, SSIM, and MSE as the common image quality metrics. To evaluate, four models were chosen, namely:

1. Bicubic Interpolation
2. SRCNN (Super-Resolution Convolutional Neural Network),
3. EDSR (Enhanced Deep Super-Resolution Network) and
4. ESRGAN (Enhanced Super-Resolution Generative Adversarial Network).

Objectives

The primary objectives of this study are as follows:

1. **Model Training and Implementation:** Implement the complete Machine Learning and Deep Learning implementation flow, which involves collecting the dataset, pre-processing the dataset, splitting the dataset and finally training the models.
2. **Performance Evaluation:** Evaluate the performance of deep learning based super resolution models in improving the quality of medical images, in particular MRI scans. In this evaluation, both quantitative and qualitative evaluation are considered.
    - *Qualitative evaluation of super-resolution MRI images*: A visual comparison of reconstructed images with the low-res images will help establish the performance and validation of perceptual quality and structural integrity of each model, and understand whether these models can preserve and improve on key radiological structures
    - *Quantitative evaluation of super-resolution MRI images*: Compare the chosen super resolution models on performance metrics like PSNR, SSIM and MSE.

II. LITERATURE REVIEW

This literature review delves into the advancements in super-resolution techniques, emphasizing their role in enhancing the quality of medical imaging.

[1], [9-11] studied the usage of 3D convolutional neural networks for super resolution of brain MRI data and showed the effectiveness of network design factors, such as optimization methods and residual learning. In addition, they also extended their approach to multimodal super resolution using inter modality priors and demonstrated promising results in real clinical settings.

In another study [2], it was shown that iterative super-resolution algorithms can be used to improve spatial resolution in 2D multi slice MRI. Isotropic resolution, which is essential for some diagnostic applications, and better edge definition in the slice select direction, resulting in better visualization and earlier diagnosis, is achieved by their method. In [3], their systematic review of super resolution techniques in brain MRI focuses on the state-of-the-art convolutional neural networks (CNNs), Generative Adversarial Networks (GANs) and Transformer based models. While advances have been made, the study also found that the maintenance of fine details at higher scaling factors is a challenge for clinical diagnostics.

A novel relation model which incorporates gradient information from multi-contrast MRI images was introduced in [4] to enhance edge details in reconstructed images. The researchers showed that this approach outperformed state of the art methods, achieving high visual and objective quality criteria including edge enhancement for low resolution observations. DeepResolve, a 3D convolutional neural network, was presented by researchers in [5] for reconstructing thin-slice knee MRIs from thick slices. We show that their model learns to interpolate in both structural similarity and peak SNR, and outperforms conventional and state of the art interpolation methods in both structural similarity and overall diagnostic quality, with substantial agreement among radiologists in diagnostic evaluations.

These challenges were overcome by [6], where the researchers introduced Fused Attentive Generative Adversarial Networks (FA-GAN) with local fusion feature blocks and global feature fusion modules which are able to provide better image quality. PSNR and SSIM values across the board were better than the contemporary methodologies, and the FA-GAN was able to reduce scan times while keeping the resolution high. Further, An adversarial learning approach based on the SRGAN model with 3D convolutions was proposed in [7] to improve volumetric MRI imaging. To improve the reconstruction accuracy, the method combined least squares adversarial loss and content loss. The results were promising with respect to perceptually convincing reconstructions and outperform classical interpolation methods with a focus on high downsampling factors. To explicitly incorporate multi contrast MRI relationship and observation models into the SR process, [8] developed a Model Guided Deep Unfolding Network (MGDUN). MGDUN outperformed conventional methods with high PSNR on both IXI and BraTs datasets by utilizing an unfolding iterative network and a well-designed objective function. It gave improved interpretability and trustworthiness in clinical settings.

Research Gap

Medical imaging based super resolution methods have many limitations. [1] and [2] used 3D CNNs and iterative algorithms to improve MRI resolution but lacked good fine details at higher scaling factors. Reconstruction challenges for preserving structural integrity were highlighted in [3], and edge enhancement was achieved using gradient based models in [4], but the generalizability was lacking. [5] was limited to thin slice reconstruction and was only applicable to knee MRI. Although current SR methods for MRI have made significant advances, little work has been done on the integration of robust perceptual quality assessment mechanisms and comprehensive cross contrast fusion strategies. To fill this gap, we propose a novel framework which combines advances in fusion models and perceptual evaluation to improve clinical applicability.

These gaps identify the need for a framework that can learn to enhance pixel level accuracy and structural details while simultaneously generalizing across various imaging modalities. We solve these challenges with an implementation that runs robustly on multiple datasets.

III. METHODOLOGY

The methodology was structured into a systematic process for super resolution of radiological structures in MRI images. This included dataset preparation, model selection, dataset splitting, model evaluation and comparative analysis. The broad-level flow followed is shown in fig 3.1.

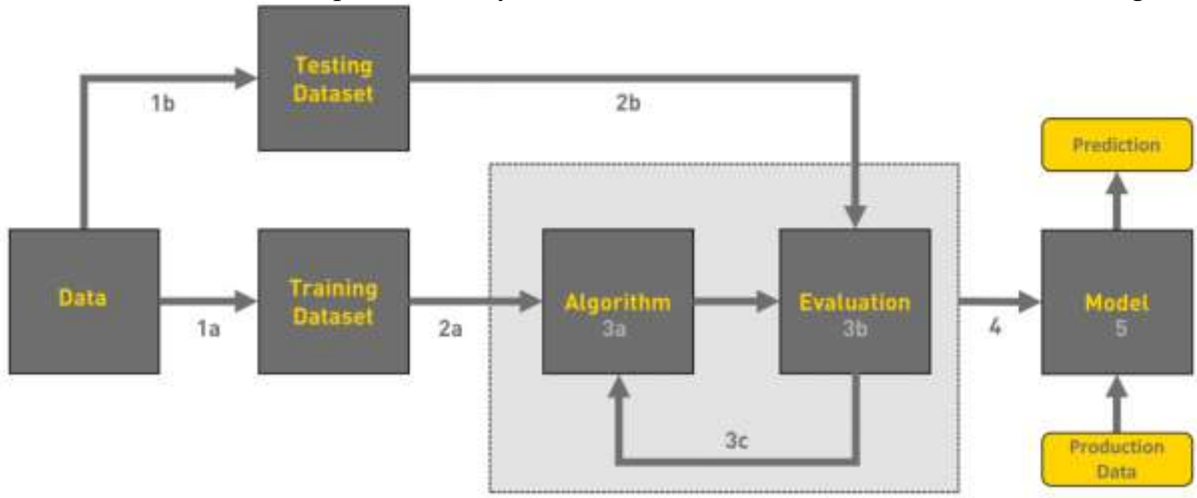


Fig 3.1: Methodology Flow

1. **Dataset Preparation**: The primary dataset considered was a dataset of low-res MRI videos. Images were sliced frame-by-frame from the MRI scan videos. For all further processing, these images were considered as the dataset.
   Pre-processing of this dataset was performed to have uniform image size and remove artifacts or noise that may hamper model's performance. The dataset was augmented further to increase the dataset diversity and to improve model generalization capabilities.
2. **Dataset Splitting**: Training and testing subsets were made from the primary dataset. A typical split ratio of 80:20 was applied, wherein the 80% images were used to train the algorithms, and remaining 20% were used to test the trained models.
3. **Algorithm Selection**: Due to its established performance in super resolution tasks, various deep learning algorithms such as Bicubic Interpolation, SRCNN, EDSR, ESRGAN were selected. The reason for choosing these algorithms specifically, is that they have different architectural approaches, and thus give a diversity of the methodology to reconstruct low-res MRI images.
4. **Evaluation of Selected Models**: Three key metrics, Peak Signal to Noise Ratio (PSNR), Mean Squared Error (MSE) and Structural Similarity Index Measure (SSIM) were used to evaluate the selected models. These metrics were chosen to provide a holistic understanding of the models' performance:
   - **PSNR** evaluates the pixel-level fidelity of the reconstructed images.
   - **MSE** measures pixel-wise accuracy by calculating the average squared difference between original and reconstructed images.
   - **SSIM** assesses the structural similarity between images, accounting for luminance, contrast, and texture.
5. **Performance Comparison**: Results of the models were compared based on PSNR, MSE and SSIM metrics. It served to help evaluate the strengths and weaknesses of each model with respect to structural preservation, perceptual quality, and pixel level fidelity. Visual quality assessments were also performed by comparing the low-resolution input, the super resolution output, and the high-resolution original image.

Rationale Behind the Evaluation Approach:

- To evaluate the models in a balanced way, multiple quantitative metrics were compared to assess how its ability to improve image quality affects diagnostic features.
- Qualitative validation of the metrics was performed through visual comparisons and insights into how well the models can recreate fine details and textures essential for medical diagnostics.
- With the inclusion of multiple algorithms, we were able to perform a diverse analysis, showing how different algorithms cope with the special problems involved in medical imaging datasets, e.g. noise, subtle contrasts, and texture preservation.

This methodology provided a robust evaluation framework that quantifies the models' performance and validates their practicality in real world medical imaging applications.

IV. RESULTS

This section presents the outcomes of applying various deep learning techniques to implement super-resolution of radiological structures in MRI images.

Total 10 videos were used for testing, with details of the evaluation as under:

Video No.	PSNR	SSIM
Test 1	23.67	0.8369
Test 2	21.07	0.7125
Test 3	20.69	0.6659
Test 4	24.15	0.8479
Test 5	22.58	0.7364
Test 6	22.13	0.7916
Test 7	21.89	0.7163
Test 8	21.67	0.8023
Test 9	22.14	0.8125
Test 10	24.44	0.8996

Table 4.1: Video testing results

4.1: Performance Metrics Comparison for different Metrics

Model	PSNR (dB)		MSE		SSIM	
	Standard result	Medical Images	Standard result	Medical Images	Standard result	Medical Images
Bicubic interpolation	23.14 - 33.66	29.05	53.61 - 210.35	80.96	0.6574 - 0.9299	0.94
SRCNN	24.52 - 33.05	28.31	73.43 - 138.56	95.89	0.7221 - 0.9581	0.96
EDSR	26.64 - 38.11	20.36	28.15 - 117.26 (L1)	1795.14	0.8033 - 0.9601	0.45
ESRGAN	20.35 - 34.82	33.75	--	82.44	1.96 -3.64 (PI)	0.98

Table 4.2: Comparison of different Models on the generated image dataset

Standard results refer to the parameter values obtained by these methods on general image datasets, while medical image results represent the evaluation of these parameters specifically on medical image datasets.

4.1.1: Interpreting Performance Comparison Based on SSIM: Structural Similarity (SSIM) Analysis

On Standard Images: The SSIM standard results indicate that ESRGAN achieves the highest structural similarity range (1.96-3.64) among the methods, closely followed by EDSR (0.80–0.96). Bicubic interpolation demonstrates comparatively poorer performance (0.6574–0.9299), while SRCNN’s SSIM range (0.72-0.95) suggests a moderate performance. We can conclude that the ESRGAN outperforms all other algorithms for standard images on SSIM metric.

On Medical Images: SSIM evaluates the structural similarity between images, considering luminance, contrast, and structure. The low SSIM of 0.45 for EDSR on medical images suggests that it struggles with structural coherence, potentially due to its sensitivity to noise and artifacts in the dataset. Bicubic interpolation performs surprisingly well with an SSIM of 0.94, indicating that it preserves structural content even if overall fidelity (as measured by PSNR) is not the best. Thus, it can be safely concluded that ESRGAN achieves the best SSIM (0.98). ESRGAN's superior SSIM highlights its ability to enhance texture and fine details critical for medical imaging.

Insights from Mean Squared Error (MSE)

MSE measures the average squared differences between pixel values, with lower values indicating better fidelity.

Bicubic interpolation achieves an MSE of 80.96, indicating moderate pixel-level accuracy for medical images. SRCNN records a higher MSE of 95.89, suggesting suboptimal recovery at the pixel level despite leveraging basic deep learning principles, possibly due to limited network depth and simplicity. With such a high MSE value of 1795.14 it is clear that EDSR does not generalize well to medical datasets, possibly as a result of a training bias or sensitivity to noise artifacts. The MSE of ESRGAN is 82.44, which is comparable to Bicubic interpolation, and shows competitive pixel level accuracy while optimizing perceptual quality. Thus, it can be concluded that ESRGAN, though not outperforming Bicubic Interpolation, still performs decently, with a low MSE value.

Insights from PSNR

On standard images: PSNR range of EDSR (26.64–38.11 dB) is highest, which implies that EDSR has better reconstruction accuracy than Bicubic interpolation and SRCNN. The latter shows a broader range, but perceives the optimal perceptual quality to a slight decrease of PSNR in comparison with EDSR.

On medical images: A reliable baseline is provided by bicubic interpolation with PSNR of 29.05 dB. SRCNN slightly under-performs with PSNR of 28.31 dB due to its limited enhancement capability in this specialized domain. PSNR of 33.75 dB is achieved by ESRGAN, which is the highest quality reconstruction among the methods tested, while EDSR shows a much lower performance (20.36 dB) due to poor generalization to medical datasets.

The results are summarized in table 4.1.

Metric	Observation	Interpretation
PSNR	ESRGAN achieves 33.75 dB on medical images, with Bicubic at 29.05 dB and SRCNN at 28.31 dB.	ESRGAN maintains strong perceptual quality with reasonable pixel-level accuracy. Bicubic and SRCNN perform moderately.
SSIM	ESRGAN achieves the highest SSIM (0.98), followed by SRCNN (0.96) and Bicubic (0.94).	ESRGAN excels at preserving structural and textural details, while Bicubic and SRCNN retain decent structural consistency.
MSE	ESRGAN and Bicubic have similar MSE scores (82.44 and 80.96), with SRCNN higher at 95.89. EDSR struggles with 1795.14.	ESRGAN optimizes perceptual loss for quality images, while EDSR's high MSE reflects poor generalization to medical image datasets.

Table 4.3: Metrics Comparison, observation and interpretation

4.2: Performance Metrics Comparison for different Models

Bicubic Interpolation Performs Well as a Baseline

Despite being a traditional non deep-learning method, Bicubic interpolation achieved a respectable SSIM of 0.94 and a low MSE of 80.96 on medical images.

Reason: Bicubic interpolation preserves the overall structural content of the images by smoothing pixel values. While it lacks the ability to enhance details like deep learning models, its simplicity and reliability ensure minimal distortion, making it a practical baseline for comparison.

EDSR Performs Poorly on Medical Images

EDSR, despite its strong performance on standard benchmarks, delivered the lowest SSIM (0.45) and the highest MSE (1795.14) on medical images.

Reason: The model's architecture is optimized for standard image datasets, which might lack the unique noise patterns and subtle contrasts of medical images. This mismatch likely led to poor generalization, making EDSR less effective in handling the complexities of medical imaging datasets.

SRCNN Balances Performance Across Metrics

SRCNN achieved a PSNR of 28.31, an SSIM of 0.96, and an MSE of 95.89, showing a balanced performance across metrics.

Reason: The relatively simple architecture of SRCNN effectively learns features from low-resolution images, offering consistent improvements in image quality without the complexity of advanced models like ESRGAN or EDSR.

ESRGAN Achieves the Best SSIM and PSNR

ESRGAN recorded the highest SSIM (0.98) and PSNR (33.75) on medical images, demonstrating its capability to preserve fine details and texture critical for radiological analysis.

Reason: The model's use of perceptual loss and adversarial training prioritizes the perceptual quality of images over pixel-level fidelity. This approach ensures that the reconstructed images are visually and diagnostically coherent, making ESRGAN particularly suitable for medical applications where subtle structural details are essential.

Summary

ESRGAN's highest SSIM, highest PSNR and relatively competitive MSE (82.44) establish it as the best model for enhancing medical images, striking a balance between perceptual quality and pixel accuracy.

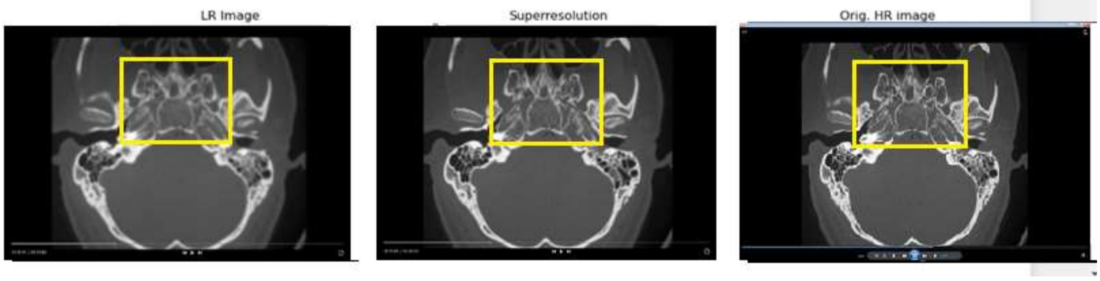
Reason: ESRGAN's ability to focus on perceptual quality ensures that critical radiological details are preserved and enhanced, which is crucial for diagnostic purposes. Its use of adversarial training also helps produce realistic textures that mimic the high-resolution ground truth more effectively than other models. The results are summarized in below table.

Model	**PSNR (dB)**	**SSIM**	**MSE**	**Key Insights**
Bicubic	29.05	0.94	80.96	Preserves structural content but lacks advanced resolution recovery capabilities.
SRCNN	28.31	0.96	95.89	Slight improvement over Bicubic due to deep learning, but struggles with pixel-level accuracy.
EDSR	20.36	0.45	1795.14	Lowest SSIM and PSNR shows its inability to generalize to medical images, and noise sensitivity.
ESRGAN	33.75	0.98	82.44	Demonstrates the best structural preservation and perceptual quality, suitable for medical images.

Table 4.4: Key Insights

4.3: Visual Quality Assessment

Figure 4.1 provides a qualitative comparison of image reconstruction:



- **Fig 4.1 (a)**: Displays the low-resolution image, demonstrating significant loss of detail and clarity, especially in fine structures essential for medical diagnostics.
- **Fig 4.1 (b)**: Represents the super-resolution image reconstructed by ESRGAN. The quality is remarkably close to the high-resolution ground truth (c), as ESRGAN successfully restores fine details and enhances textures.
- **Fig 4.1 (c)**: Shows the original high-resolution image, serving as a reference.

The enhancement of key details in (b) as compared to the original image (c) visually validates ESRGAN's superior performance in medical image super-resolution.

Key Observations

- ESRGAN demonstrates a strong balance between perceptual quality and structural integrity, as evidenced by the highest SSIM and the visual similarity between its output and the ground truth.
- The method's use of perceptual loss during training contributes to its ability to reconstruct fine textures and structural details critical for medical imaging.

In summary, ESRGAN not only outperforms other methods in structural similarity and perceptual quality but also proven effective in real-world scenarios, as shown in the visual analysis.

V. DISCUSSION

This study evaluated the effectiveness of various super-resolution models on radiological structures in MRI images using deep learning techniques. Metrics such as PSNR, SSIM, and MSE were used to compare models, with specific attention to their performance on medical images.

5.1: Summary of the Findings

Quantitative Performance Analysis

Peak Signal-to-Noise Ratio (PSNR): We find that ESRGAN is the best-performing model in PSNR with a score of 33.75 dB. This illustrates the better ability of this system to recreate and improve medical images. PSNR values of 29.05 dB for Bicubic interpolation and 28.31 dB for SRCNN were found to be in moderate effectiveness. However, EDSR suffered greatly, with a PSNR value of ~20.36 dB, indicating its limited flexibility in dealing with unique noise patterns and hardness of medical imaging datasets.

Structural Similarity Index (SSIM) and Mean Squared Error (MSE): Regarding SSIM, ESRGAN produced a score of 0.98, a tremendous performance given it was able to preserve and preserve the structural and textural details, the most important for accurate diagnostics. SRCNN and Bicubic interpolation did pretty well, with SSIM of 0.96 and 0.94 respectively, but could not match ESRGAN's fine detail ability. However, EDSR showed a low SSIM of 0.45, which is the result of the difficulty of EDSR in preserving structural consistency in medical images. Bicubic interpolation and ESRGAN showed similar results in MSE analysis, with scores of 80.96 and 82.44, respectively, yielding high pixel level accuracy. With MSE 95.89, SRCNN was lower than EDSR which was the worst with a huge MSE of 1795.14, further confirming SRCNN's inability to generalize to medical datasets.

Visual Quality Assessment

Further validation through visual comparison showed that ESRGAN's reconstructed images were as close as possible to high resolution ground truth. ESRGAN is the most effective model in this study because the fine structural details and textures restored are vital to radiological imaging.

5.1.3: Interpretation of Results

The results show that even though Bicubic interpolation is a good baseline for traditional methods with minimal distortion, it doesn't perform well with respect to advanced resolution recovery. Deep learning models such as ESRGAN and SRCNN enhance image quality significantly, with ESRGAN excelling due to its focus on perceptual quality through adversarial training. Conversely, EDSR, despite its benchmark success, struggles to adapt to medical datasets, underscoring the importance of dataset-specific optimization in medical imaging applications.

5.2: Challenges Faced

Several challenges were encountered during this study:

- **Training Time for Videos:** Training the deep learning models, particularly ESRGAN, was computationally intensive and time-consuming.
- **GPU Speed:** The available GPU resources-imposed limitations on processing speed, affecting the scalability of training and testing.
- **Limited Epochs:** Due to resource constraints, the models were trained for a limited number of epochs, which might have impacted the overall optimization and performance.

5.3: Future Scope

1. **Model Optimization for Medical Data:** Future work could involve fine-tuning architectures like EDSR to improve their adaptability to medical datasets, addressing the noise and subtle contrast issues observed.
2. **Integration with Clinical Workflows:** Extending the application of these models to real-world scenarios, such as automated diagnostics or assisting radiologists in interpreting low-resolution images, could enhance clinical utility.
3. **Resource-Efficient Training:** Developing lighter, resource-efficient models capable of delivering high-quality super-resolution without extensive computational demands will be a key area of focus.
4. **Expanding Datasets:** Incorporating diverse and larger medical datasets for training could improve model generalization and robustness, ensuring consistent performance across various imaging scenarios.

VI. CONCLUSION

This work implements super-resolution for medical images using various deep learning models, with a focus on MRI radiological structures. The findings demonstrate that ESRGAN achieves the highest SSIM of 0.98, PSNR of 33.75 dB, and a competitive MSE of 82.44 among other methods. This shows that ESRGAN is very good at improving both perceptual quality and structural coherence, and thus very well suited for medical imaging application where subtle textural and structural details are important for accurate diagnosis. On the other hand, deep-learning based models exhibited high resolution recovery capabilities but had a solid baseline provided by traditional methods such as Bicubic interpolation. SRCNN performed balanced, and EDSR, although performing better on standard benchmarks, failed to generalize to the novel challenges of medical datasets.

This study demonstrates the need for specialized deep learning models for medical imaging, where the noise patterns and contrast nuance of these datasets are idiosyncratic to the task at hand. Future work can involve better tailoring architectures like EDSR to medical applications or hybrid approaches that combine the best of models like ESRGAN with pixel level fidelity methods. Moreover, the analysis can be extended to larger and more varied medical datasets to further validate these findings and drive further medical image super resolution improvements, improving diagnostic accuracy and clinical decision making.

REFERENCES

[1] Pham, Chi-Hieu, et al. "Multiscale brain MRI super-resolution using deep 3D convolutional networks." *Computerized Medical Imaging and Graphics* 77 (2019): 101647.

[2] Greenspan, Hayit, et al. "MRI inter-slice reconstruction using super-resolution." *Magnetic resonance imaging* 20.5 (2002): 437-446.

[3] Muhammad, Abdulhamid, et al. "Brain MRI Image Super-Resolution Reconstruction: A Systematic Review." *IEEE Access* (2024).

[4] Zheng, Hong, et al. "Multi-contrast brain MRI image super-resolution with gradient-guided edge enhancement." *IEEE access* 6 (2018): 57856-57867.

[5] Chaudhari, Akshay S., et al. "Super-resolution musculoskeletal MRI using deep learning." *Magnetic resonance in medicine* 80.5 (2018): 2139-2154.

[6] Jiang, Mingfeng, et al. "FA-GAN: Fused attentive generative adversarial networks for MRI image super-resolution." *Computerized Medical Imaging and Graphics* 92 (2021): 101969.

[7] Sánchez, Irina, and Verónica Vilaplana. "Brain MRI super-resolution using 3D generative adversarial networks." *arXiv preprint arXiv:1812.11440* (2018).

[8] Yang, Gang, et al. "MGDUN: An interpretable network for multi-contrast MRI image super-resolution reconstruction." *Computers in Biology and Medicine* 167 (2023): 107605.

[9] Van Reeth, Eric, et al. "Super-resolution in magnetic resonance imaging: a review." *Concepts in Magnetic Resonance Part A* 40.6 (2012): 306-325.

[10] Yue, Linwei, et al. "Image super-resolution: The techniques, applications, and future." *Signal processing* 128 (2016): 389-408.

[11] Qiu, Defu, Yuhu Cheng, and Xuesong Wang. "Medical image super-resolution reconstruction algorithms based on deep learning: A survey." *Computer Methods and Programs in Biomedicine* 238 (2023): 107590.

[12] Peeters, Ronald R., et al. "The use of super-resolution techniques to reduce slice thickness in functional MRI." *International Journal of Imaging Systems and Technology* 14.3 (2004): 131-138.

[13] Li, Hongbi, et al. "Multi-level feature extraction and reconstruction for 3D MRI image super-resolution." *Computers in Biology and Medicine* 171 (2024): 108151.

[14] Plenge, Esben, et al. "Super-resolution methods in MRI: can they improve the trade-off between resolution, signal-to-noise ratio, and acquisition time?." *Magnetic resonance in medicine* 68.6 (2012): 1983-1993.

[15] Isaac, Jithin Saji, and Ramesh Kulkarni. "Super resolution techniques for medical image processing." *2015 International Conference on Technologies for Sustainable Development (ICTSD)*. IEEE, 2015.