Reviewer 1.

MAJOR CONCERNS

Given the wide variety of Super-Resolution (SR) techniques available, could you explain why the study focuses on only a small subset of these algorithms? How were these specific techniques chosen, and what makes them particularly relevant for comparison? It would be valuable to address how this selection impacts the study's overall relevance to the field.

Resp: The study's focus on a small subset of super-resolution (SR) algorithms is driven by several key considerations that enhance its relevance and applicability to the field of medical imaging, particularly in the context of improving vascular structure visualization in computed tomography angiography (CTA) images. Moreover, the selected super-resolution algorithms enhance the study's relevance by ensuring that the chosen techniques are not only effective but also applicable to the specific challenges of medical imaging. This targeted approach allows for a more in-depth analysis of each algorithm's strengths and weaknesses, ultimately contributing to improved diagnostic capabilities and patient care in the field of vascular imaging. Here's a detailed explanation of the selection process and its implications:

1. The algorithms chosen—such as SRCNN, EDSR, RCAN, SRGAN, and ESRGAN—are specifically relevant to the challenges of enhancing the resolution of biological images from nature which are complex as medical images as it is reported in the literature reviewed. For this research work, the models have been adapted from their original design for natural images to address the unique characteristics of CTA images, which often include noise, low contrast, and the need for high spatial resolution to visualize small blood vessels effectively (as it is detailed in introduction and when different methods are described).
2. The selected algorithms have demonstrated strong performance in previous studies, particularly in terms of metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). By focusing on models that have shown promise in enhancing image quality, the study can provide a more reliable comparison of their effectiveness in a medical context (section 3.5).
3. The subset includes a variety of approaches—ranging from convolutional neural networks (CNNs) to generative adversarial networks (GANs)—which allows for a comprehensive evaluation of different methodologies. This diversity is crucial for understanding how different architectural choices impact the quality of super-resolved images, particularly in the context of vascular imaging (section 2).
4. Given the computational demands of training and evaluating deep learning models, focusing on a smaller number of algorithms allows for a more thorough exploration of each one. This ensures that the study can effectively utilize available resources while still providing meaningful insights into the performance of each technique (introduction).
5. The selected algorithms are particularly relevant for clinical applications, as they address specific needs in the visualization of vascular structures. For instance, the ability of SRGAN to generate high-frequency details makes it suitable for enhancing the visibility of small arteries, which is critical for diagnosing conditions like peripheral arterial occlusive disease (Conclusions).

6. The choice of these specific techniques is also informed by existing literature, which has established a foundation for their use in medical imaging. By building on prior research, the study can contribute to a growing body of knowledge while also identifying gaps that may warrant further investigation (Related Works).
7. Finally the selection was made after a deep and methodological search technique in order to select from the literature the best techniques with better performance and using deep learning or generative models. Considering the whole universe of techniques makes no sense for our research.

You mentioned the goal of demonstrating the role of SR techniques in DSS, but it would be beneficial to elaborate on what specific role these techniques play. How do they integrate into a DSS, and in what ways do they improve efficiency or reduce costs? More detail on this would greatly enhance the clarity of the study's objectives.

Resp: We added a Section 2 "Impact of including SR techniques in DSS in health-systems" where we describe in detail the role of the SR techniques in DSS, including how they can be integrated to a clinical environment and how they can improve the efficiency and reduce cost, even when this are not the scope of this chapter but to make it clear.

The paper mentions dividing models into several groups, but it would be helpful to clarify the criteria used for these classifications. What defines a residual model versus a scaling model? For instance, why are LapSRN and SRDenseNet classified as residual models with new scaling methods? A more detailed explanation would strengthen the study's framework.

Resp: Both methods use residual networks and the strategy of scaling networks capacity to improve the results. At the beginning of each classification criteria studied and reviewed from literature, we add a description of the criteria. This makes clear the classification.

In the "Development Tools" section, several libraries are mentioned that require specific citations. Could you please ensure that these references are included, as many main library pages request citing particular papers when their tools are used, such as scikit-learn?

Resp: You are right and we include them in the reference list..

In the "Evaluation metrics" section, you mention that SSIM can be negative. Could you elaborate on what a SSIM value of -1 represents?

Resp: We describe the cases when the value is 0 and 1, but not when it is -1, we clarify this by adding the meaning of a SSIM value of -1.

Additionally, could you clarify the meaning behind the numbers used in models like SRCNN 9-1-5, SRCNN 9-5-5, and codes like f64k9s1, f64k1s1, etc.?

In the discussion regarding 3D representation, you mention "we perform a 3D representation of the images obtained and we can see how the small arteries gain light due to the effect of the SR, as we can see in Figures 10, 11, and 12." Are these figures indeed 3D representations? If so, it would be helpful to explain this clearly as the figures currently appear to contain artifacts and seem to be 2D representations. A more detailed explanation would be appreciated.

Resp: They are a frontal view from a 3D rendering process after the superresolution application. These 3D representations were generated with the application open source Slice3D. We added an explanation in place when making reference to them.

MINOR CONCERNS
Could you please explain Figure 9 further? The figure is described as a "Diagram of bicubic interpolation algorithm," but more detail would help clarify its significance.

Resp: It was clarified

There are a few typographical errors, such as "AAdditionally." It would be beneficial to review the text for such errors to ensure clarity and professionalism.

Resp: Solved

Correct Verb Tense:
In the sentence "Initially, most SISR reconstructions are based on sample learning," it seems that "are" should be replaced with "were" to correctly reflect the past tense, since you are talking of the past.

Resp: Changed

The sentence "These SR methods focus on dictionary learning and optimization or model building and are rarely optimized" might be confusing. Perhaps a rewording would help clarify what is meant by optimization here.

Resp: It was clarified

Reviewer 2.

MINOR CONCERNS

The phrase "the PSNR and SSIM were very good" would be more informative with specific values or a more detailed explanation of what constitutes "very good" in this context.

Resp: It was clarified

The paper references a "sister model" of SRCNN. Could you specify which model this refers to and how it relates to SRCNN? why is its "sister"?

Resp: It was clarified

Could you provide a brief explanation of the 'tanh' activation function for clarity, especially for readers who may not be familiar with this term?

Resp: We added, and also added a reference to