Medical Image Enhancement Using CLAHE and Pelican Optimization

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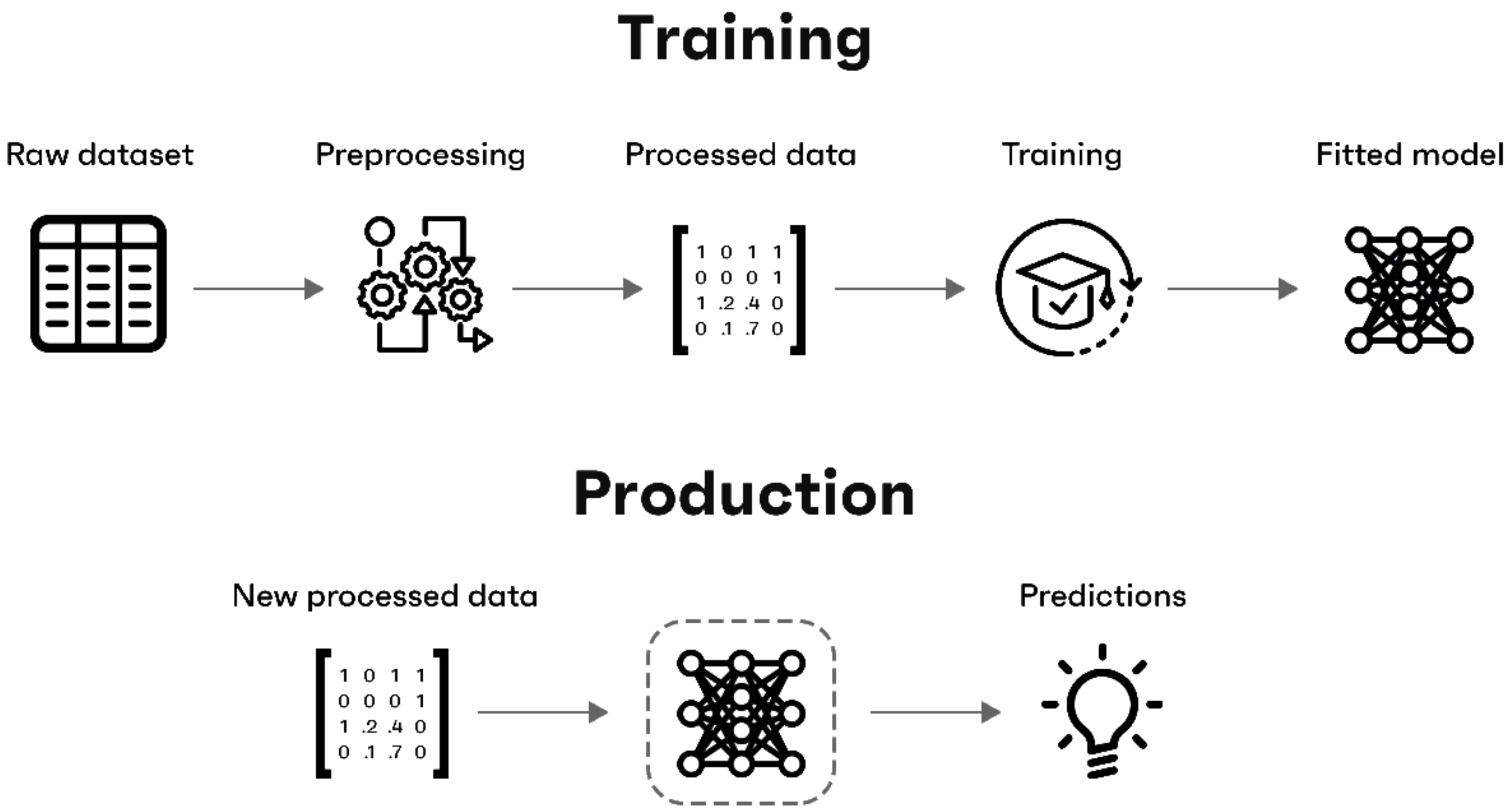
What is image enhancement?



Why do we need image enhancement?

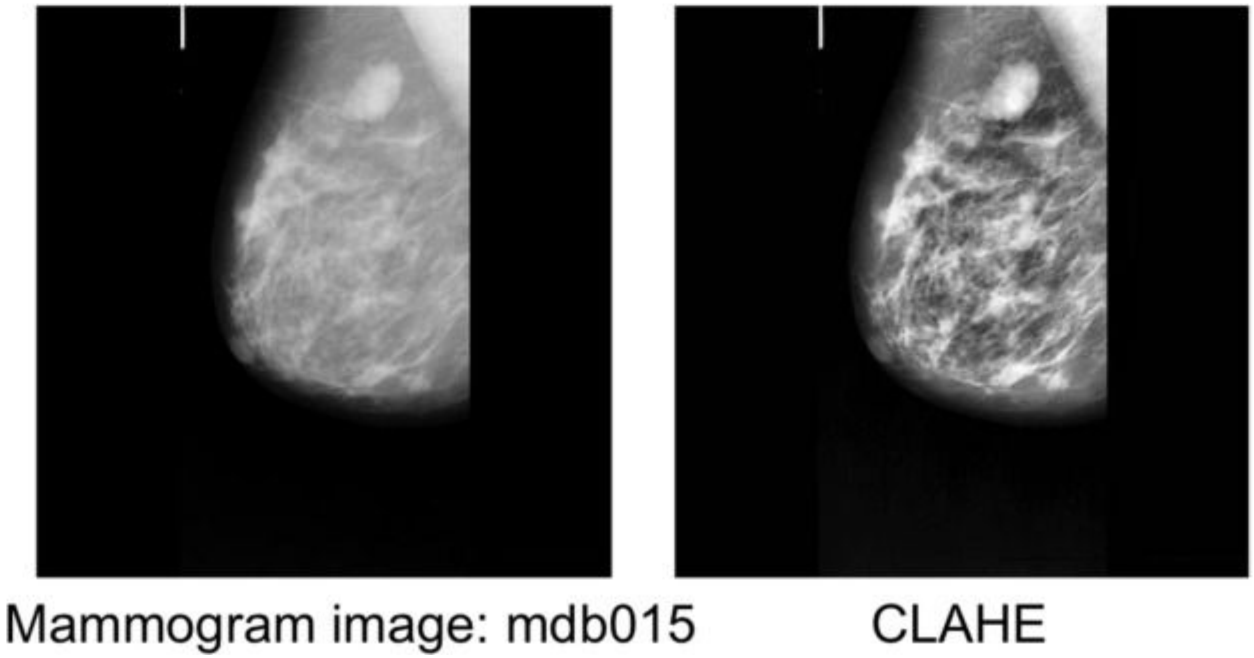


Figure 1. Image enhancement using CLAHE. Taken from [1]

Goals/ claims of this paper

The overall objective of this paper is to present a novel medical image enhancement method. This model is based on using POA to estimate the clip-limit, which controls the performance of the enhancement operation using CLAHE. The estimation process improves the efficiency of the operation and provides superior results in terms of image quality and contrast. The utilization of the present algorithm allows gaining a superior visual impact on the processed image as well as increasing the conformity rate in the clinical diagnosis.

Figure 2. Excerpt taken from original paper. Taken from [2]

Contrast Limited Adaptive Histogram Equalization (CLAHE)

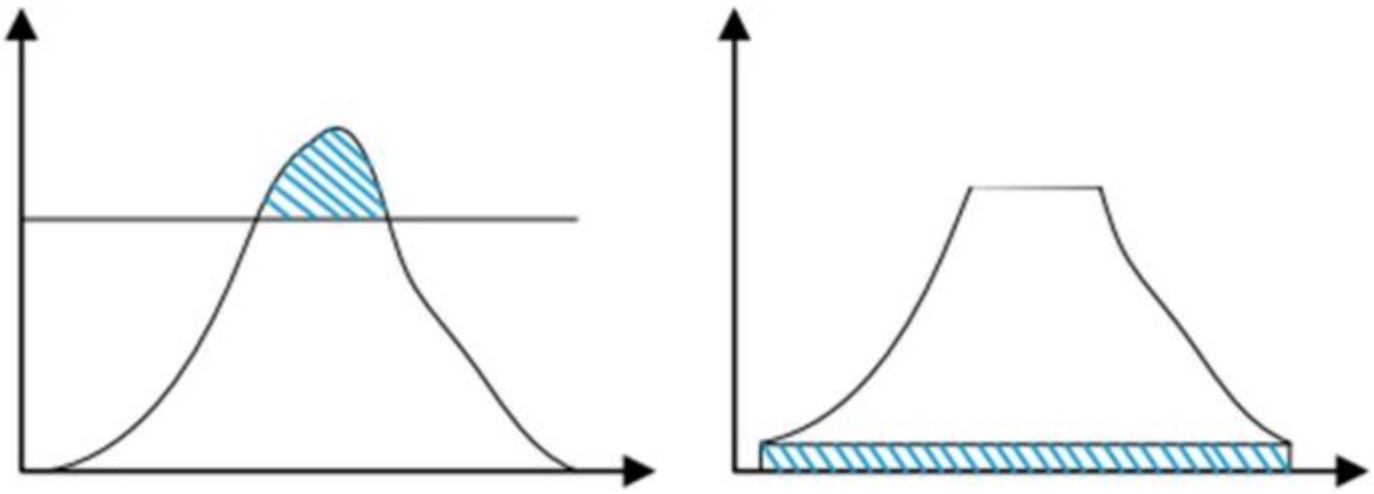


Figure 3. Working mathematical principle of CLAHE. Taken from [2]

Contrast Limited Adaptive Histogram Equalization (CLAHE)

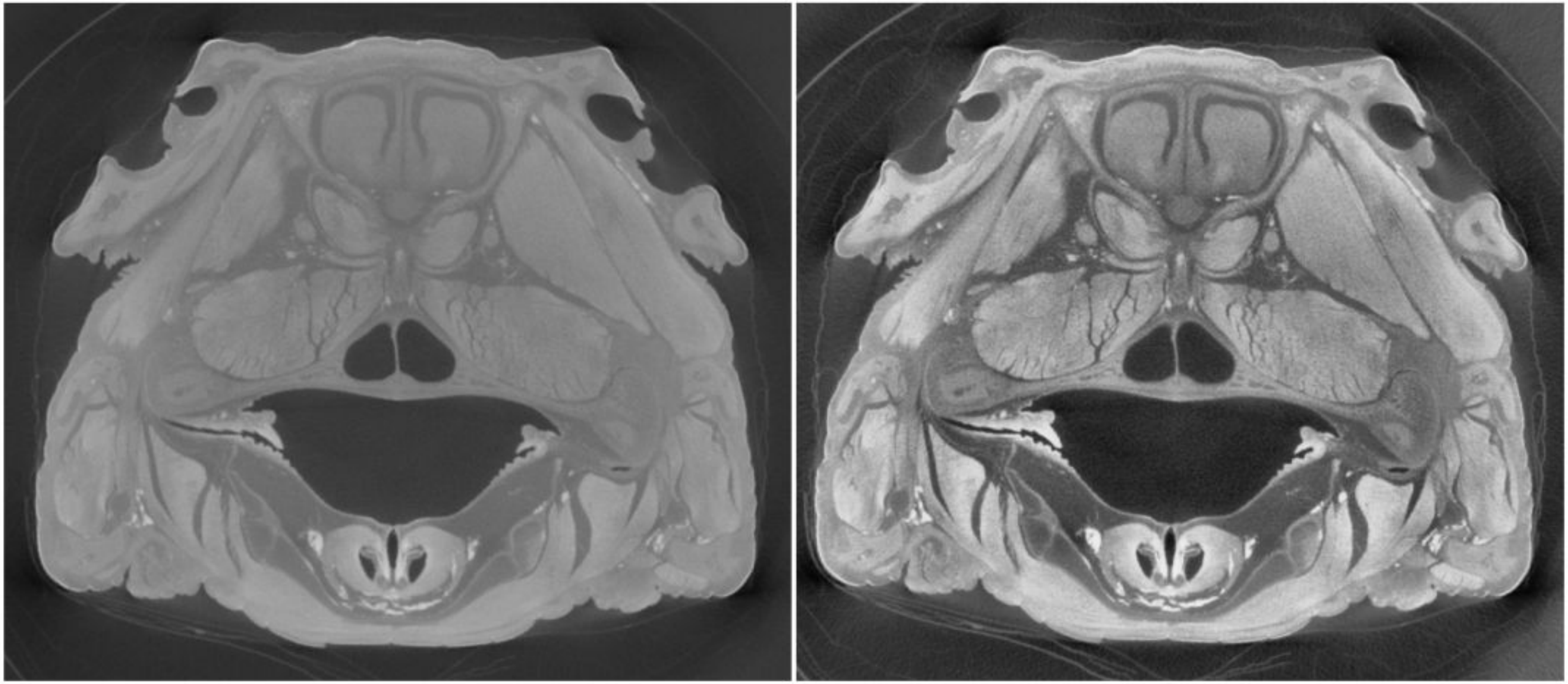


Figure 3. Another example of CLAHE application in images

Pelican Optimization Algorithm (POA)

$$X = \begin{bmatrix} X_1 \\ \cdot \\ X_i \\ \cdot \\ X_N \end{bmatrix}_{N*m} = \begin{bmatrix} x_{1,1} & x_{1,j} & x_{1,m} \\ x_{i,1} & x_{i,j} & x_{i,m} \\ x_{N,1} & x_{N,j} & x_{N,m} \end{bmatrix}_{N*m}$$

$$F = \begin{bmatrix} F_1 \\ \cdot \\ F_i \\ \cdot \\ F_N \end{bmatrix}_{N*1} = \begin{bmatrix} F(X_1) \\ \cdot \\ F(X_i) \\ \cdot \\ F(X_N) \end{bmatrix}_{N*1}$$

$$x_{i,j} = l_j + rand.\left(u_j - l_j\right)$$

$$i = 1, 2, \ldots, N, j = 1, 2, \ldots, m,$$

- Peak Signal-To-Noise Ratio (PSNR)
- Structural Similarity Index (SSIM)
- Correlation Coefficient (CoC)
- Mean Square Error (MSE)
- Entropy (EL)
- Standard Deviation (SD)

Pelican Optimization Algorithm (POA)

$$x_{i,j}^{P_1} = \begin{cases} x_{i,j} + \text{rand} \cdot \left(p_j - I \cdot x_{i,j}\right), & F_p < F_i; \\ x_{i,j} + \text{rand} \cdot \left(x_{i,j} - p_j\right), & \text{else} \end{cases}$$

$$X_i = \begin{cases} X_i^{P_1}, F_i^{P_1} < F_i \\ X_i, \text{else} \end{cases}$$

Pelican Optimization Algorithm (POA)

$$x_{i,j}^{P_2} = x_{i,j} + R \cdot \left(1 - \frac{t}{T}\right) \cdot (2 \cdot rand - 1) \cdot x_{i,j}$$

$$X_i = \begin{cases} X_i^{P_2}, F_i^{P_2} < F_i \\ X_i, \text{else} \end{cases}$$

Original Paper Proposed Method

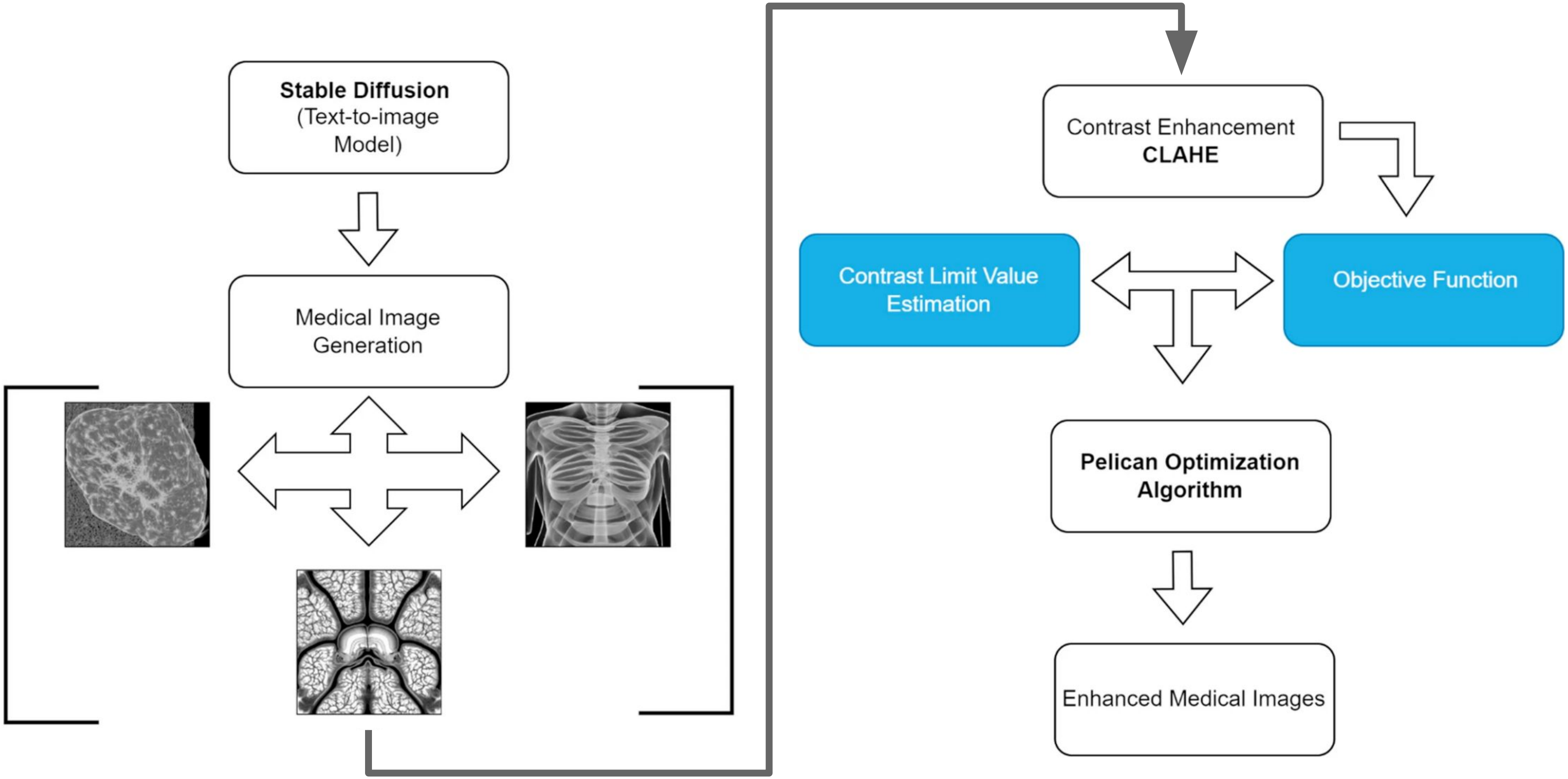
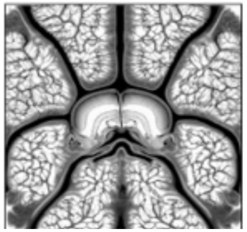


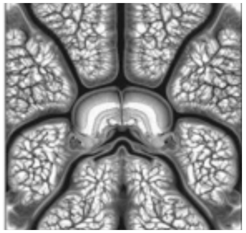
Figure 3. The steps of the image enhancement operation. Taken from [2]

Paper Original Proposed Method

Create Data	Use stable diffusion to create grey images
β Estimation	After testing they estimate β (Eqn 10)
POA for β	Find best β using POA
CLAHE	Apply CLAHE with found β



→ β Estimation → POA for β



Paper Original Comparative Analysis

Compared with eight state-of-the-art experimental methods:

- Wiener Filter (WF)
- Gaussian Filter (GF)
- Median Filter (MF)
- Quantum Particle Swarm Optimization algorithm (QPSO)
- Artificial Bee Colony Algorithm (ABC)
- Unsharp Masking Algorithm (UM)
- CSDNET model
- FilterNet model

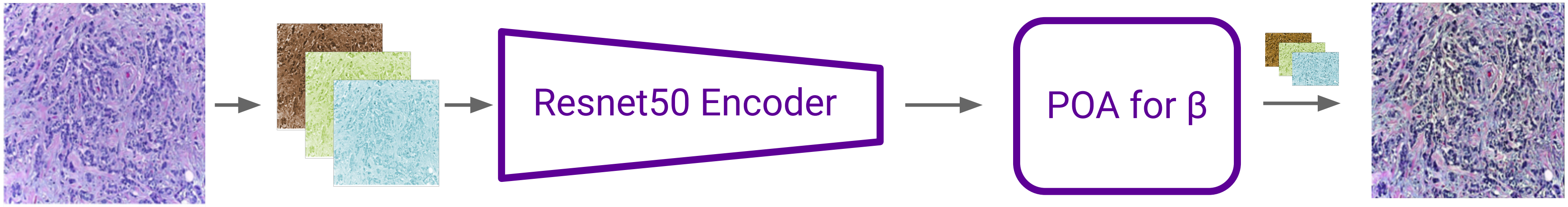
Paper **Extension** Proposed Method

Retrieve Data — Retrieve RGB histological images

Feature Encoder — Encode images in Resnet50 feature space for encoded representation

POA for β — Find best β using POA

CLAHE — Apply CLAHE with found β



Reproduction of Original Results

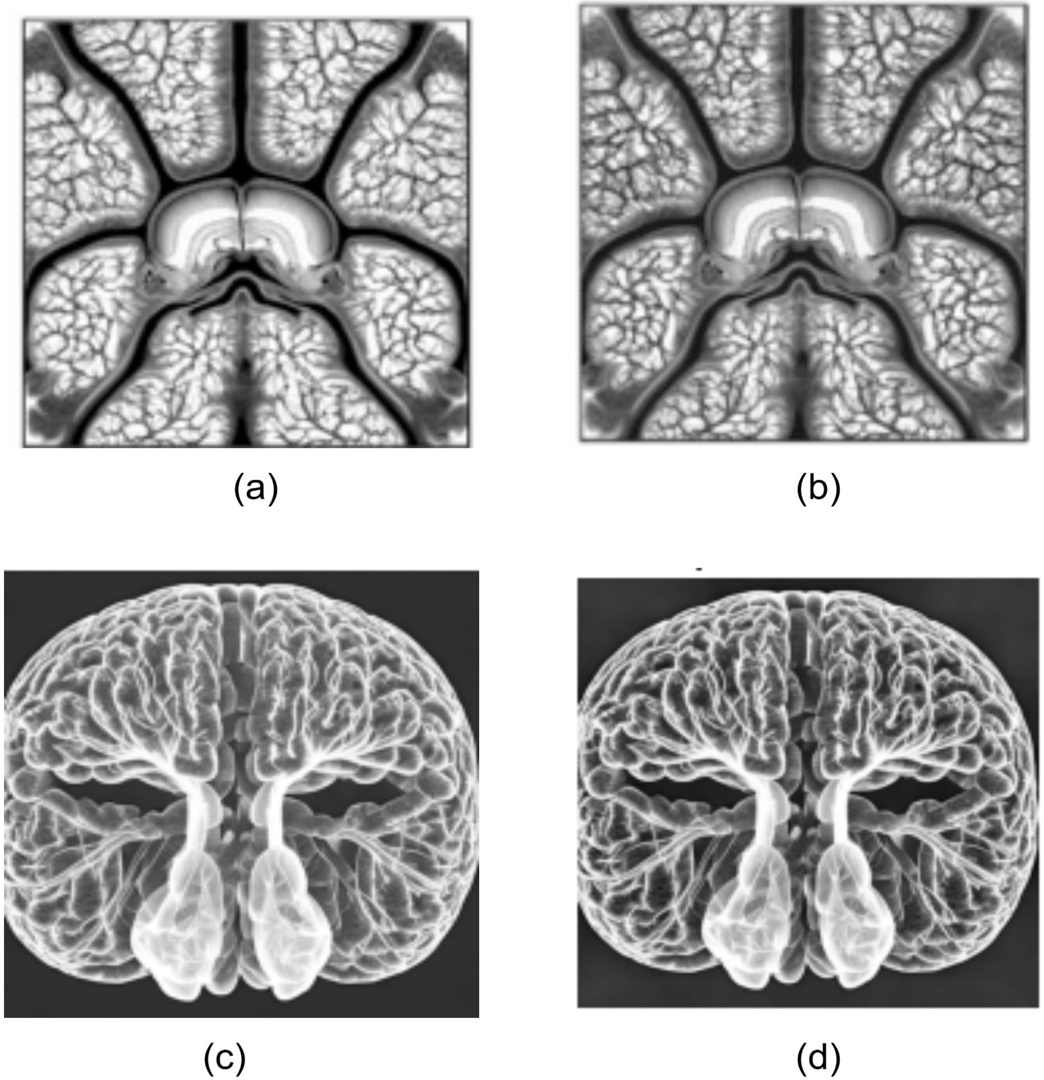


Figure 4. Comparison of image enhancement results. Images (a) and (b) represent results from the original study [2], while images (c) and (d) are generated using our implementation of the original algorithm on synthetic datasets.

Reproduction of Original Results

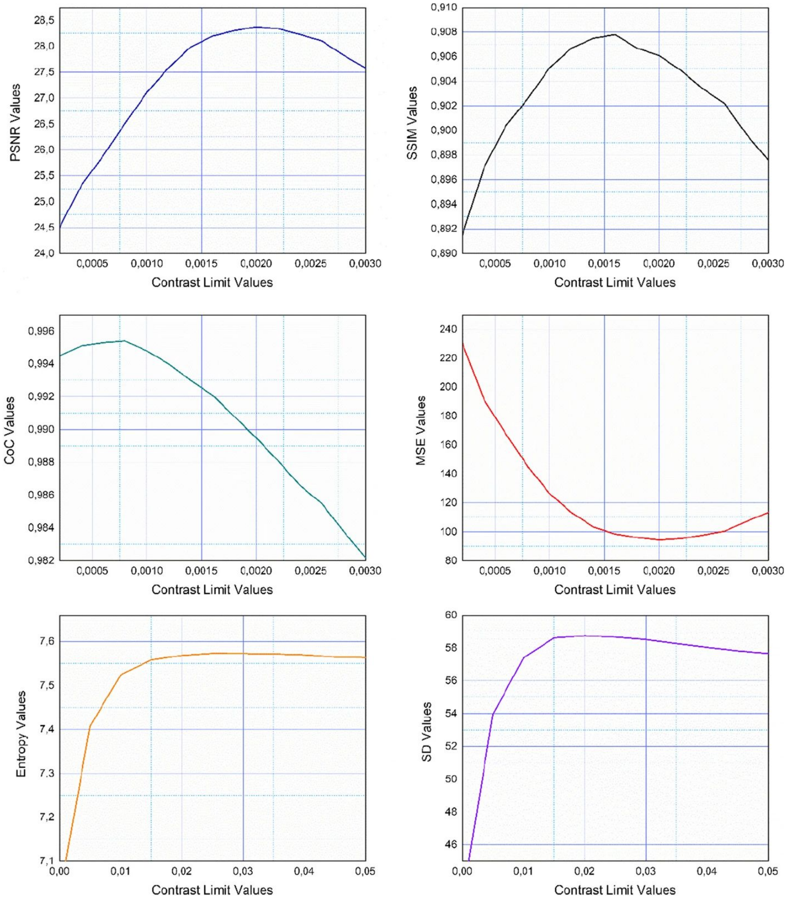


Figure 5. The variation of the clip limit with the performance parameters of the original paper. Taken from [2].

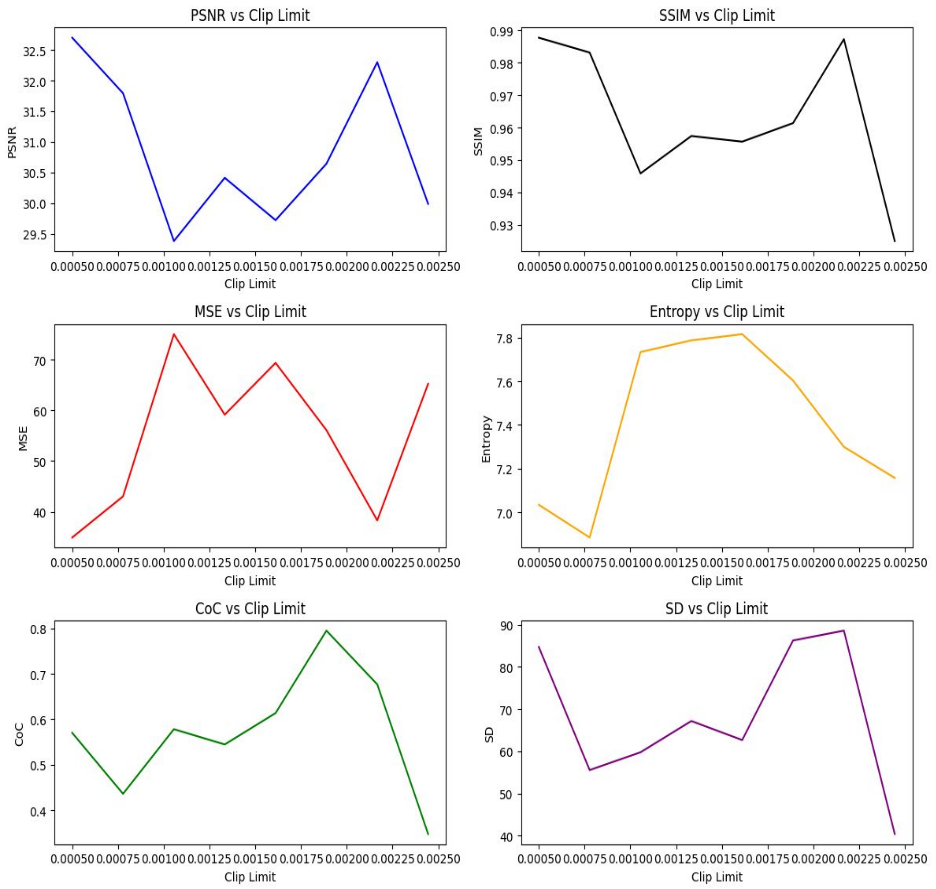


Figure 6. The variation of the clip limit with the performance parameters of the implementation of the original paper.

Extension to Original Work

The original work was extended in 2 contexts:

1. Extending the algorithm
2. Extending the dataset

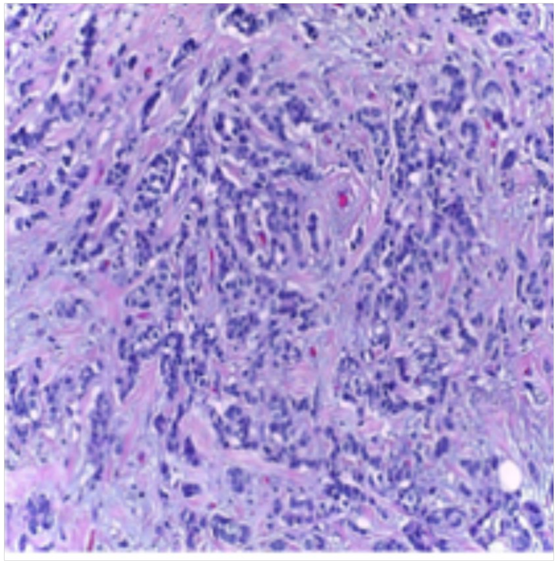


Figure 7. Original image from the Bach Breast Cancer Histology dataset

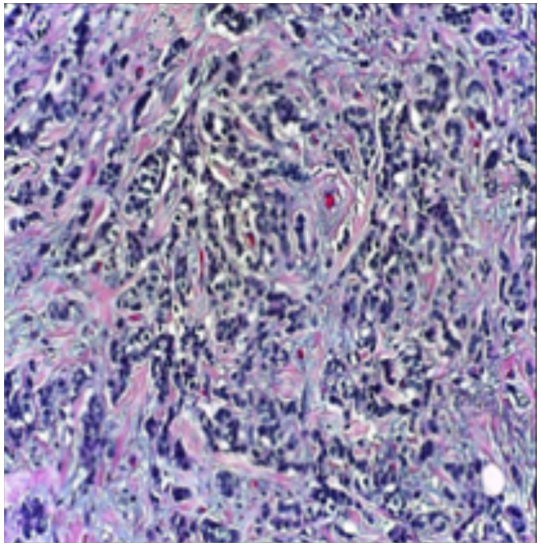


Figure 8. Enhanced image using the extended algorithm

Comparative Study with State-of-the-Art Models

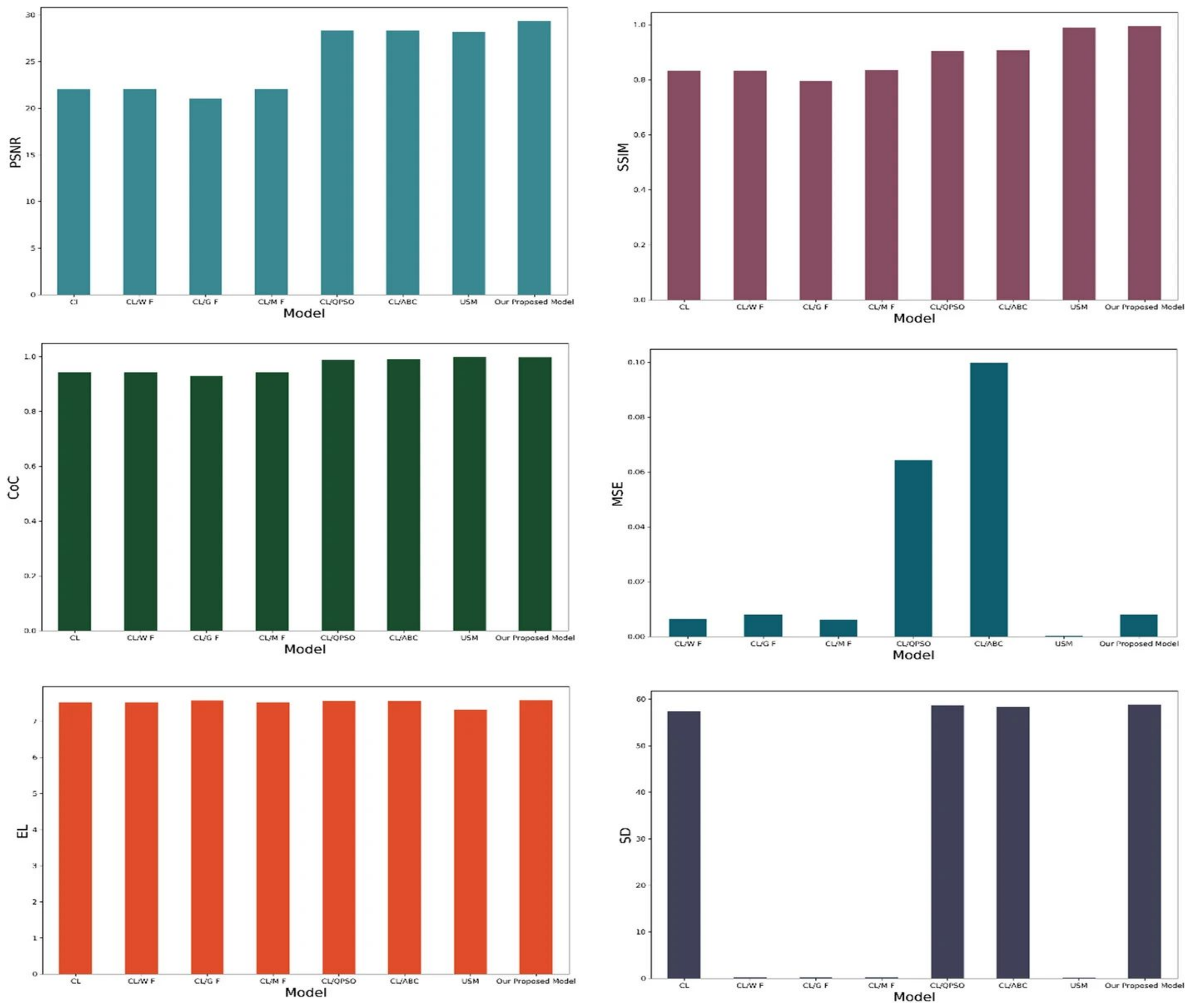


Figure 9. Comparison of the enhancement efficiency using the proposed model from the original paper and other experimental methods. Taken from [2]

Comparative Study with State-of-the-Art Models

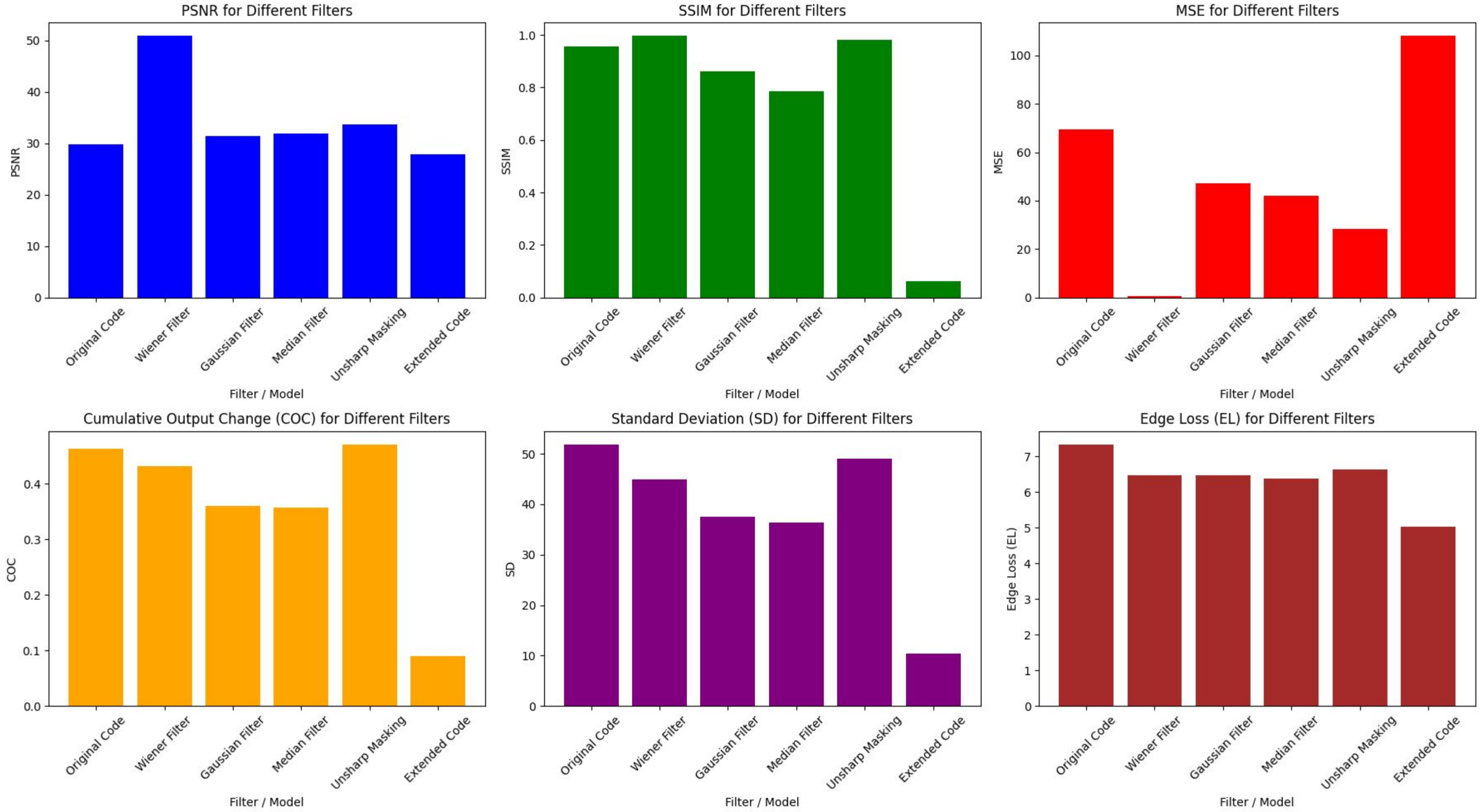


Figure 10. Comparison of the enhancement efficiency using original implementation, extended work and other experimental methods on the synthetic dataset

Comparative Study with State-of-the-Art Models

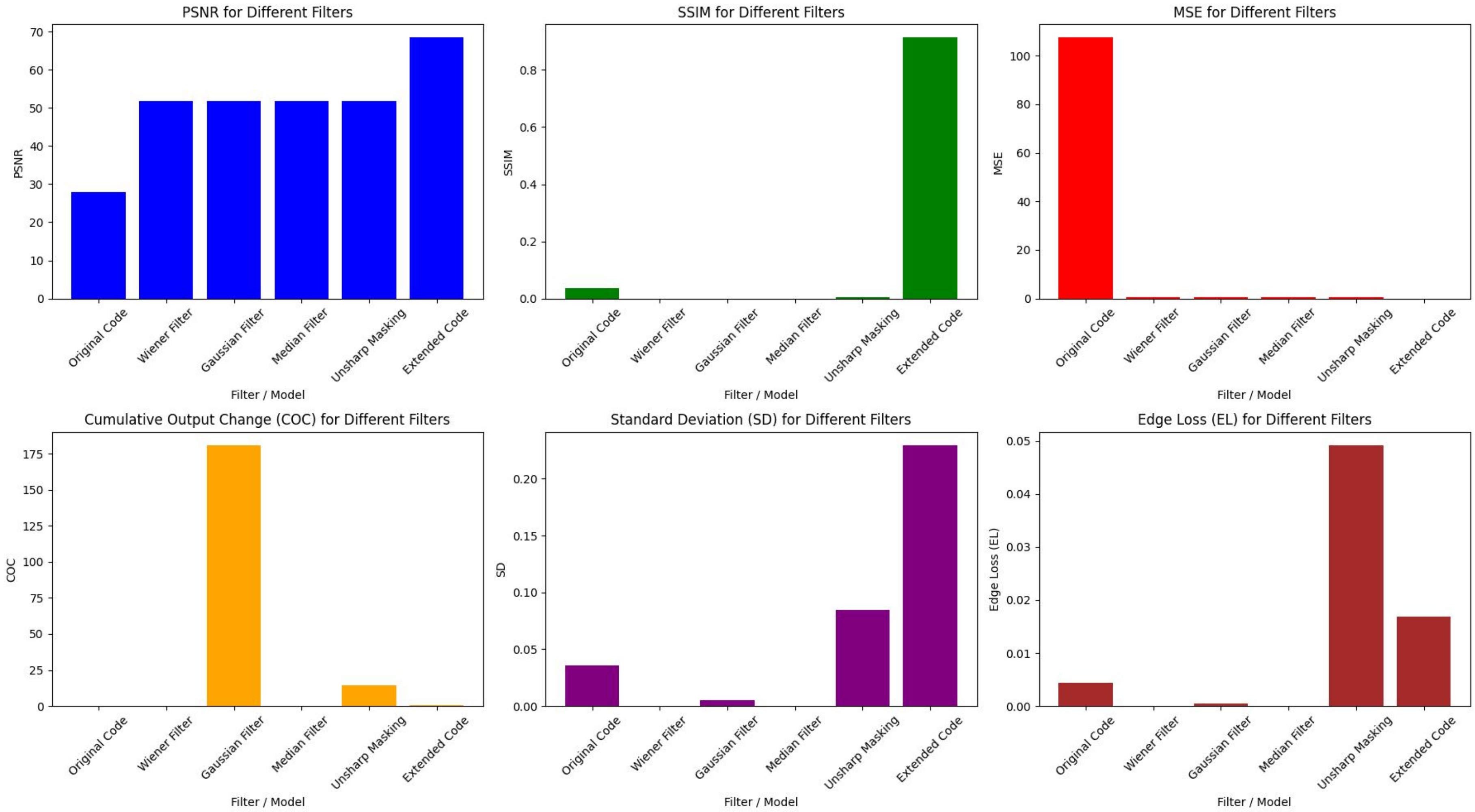


Figure 11. Comparison of the enhancement efficiency using original implementation, extended work and other experimental methods on the histology dataset

Successes, Challenges, Limitations, and Future Investigations

- Successes:
  - Enhanced Image Quality: CLAHE + POA improved edge sharpness and detail preservation across CT, MRI, PET, and histology images.
  - Versatility: Adapted well to histology images, demonstrating the algorithm's robustness.
- Challenges:
  - Dataset Constraints: Unable to access the original dataset; used synthetic datasets, introducing noise variations.
  - Histology Image Complexity: The fine structures in histology images posed additional challenges, increasing computational demands.
- Limitations:
  - Noise vs. Contrast: Higher MSE indicates a trade-off between contrast enhancement and noise.
  - Computational Load: 3D histology images added significant complexity, highlighting the need for optimization.
- Future Work:
  - Real-World Datasets: Essential for validating the algorithm's performance.
  - Optimization: Focus on reducing computational overhead.
  - Domain-Specific Adjustments: Tailor the algorithm for specific medical imaging tasks.

Conclusion

- The study introduced a novel image enhancement algorithm combining CLAHE with POA to improve medical images across different modalities.
- The algorithm tackled challenges like noise reduction, contrast improvement, and computational efficiency, showing promising results in CT, MRI, PET scans, and histology images.
- The extension to histology images enhanced the method's ability to preserve cellular details and contrast, making it effective for complex tissue analysis.
- Performance metrics were improved by integrating feature-based metrics, specifically designed for histology image characteristics.
- Computational complexity, especially with 3D histology images, highlighted the need for further optimization and scalability in future work.
- CLAHE + POA demonstrated substantial improvements in medical image quality and diagnostic relevance, particularly in histology images.
- Future research could focus on optimizing the algorithm further, using diverse real-world datasets, and exploring hybrid approaches for better computational efficiency.

1. Pawar, M., & Talbar, S. (2021). Local entropy maximization based image fusion for contrast enhancement of mammogram. *Journal of King Saud University-Computer and Information Sciences*, *33*(2), 150-160.
2. Haddadi, Y. R., Mansouri, B., & Khodja, F. Z. I. (2024). A novel medical image enhancement algorithm based on CLAHE and pelican optimization. *Multimedia Tools and Applications*, 1-20.

Thank You