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# Implementation of Laplacian-Based Image Sharpening on X-Ray Images

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**Abstract:** X-ray imaging plays an essential role in modern medical diagnostics; however, the resulting images often suffer from low contrast and unclear edge structures. These limitations reduce anatomical visibility and may negatively affect diagnostic accuracy. Therefore, there is a need for a simple, effective, and computationally efficient image enhancement method that can improve X-ray image sharpness while preserving critical diagnostic information. **Objective**: This study aims to implement and analyze the Laplacian method for enhancing the sharpness of chest X-ray images using digital image processing techniques based on Python and OpenCV. The study also evaluates the effectiveness of the proposed method in improving the visibility of anatomical structures in radiographic images. **Methodology**: This research adopts a quantitative experimental approach based on computational implementation. The dataset consists of digital X-ray images processed through several stages, including image acquisition, grayscale conversion, Laplacian filtering, image sharpening, and result visualization. The entire implementation is conducted using Python and OpenCV in the Google Colab cloud computing environment. Data analysis is performed using a descriptive-visual approach by comparing original and enhanced images. **Findings**: The results show that the Laplacian method significantly improves edge visibility in X-ray images. Anatomical structures such as ribs, lung boundaries, and fine edge details become more distinguishable compared to the original images. Local contrast enhancement is also observed, indicating that high-frequency information is effectively amplified. However, a slight increase in noise is detected due to the sensitivity of the Laplacian operator to high-frequency components. **Implications**: The findings suggest that the Laplacian method can be effectively used as a lightweight preprocessing technique for medical image enhancement, particularly in cloud-based environments such as Google Colab. The method is suitable for educational purposes, research applications, and engineering systems that require low computational cost while maintaining effective image enhancement performance. **Originality**: The originality of this study lies in the development of a simple, reproducible, and cloud-based implementation framework for Laplacian-based X-ray image enhancement using Python and OpenCV. The main contribution is a lightweight computational approach that balances implementation simplicity with effective image sharpening performance.

**Keywords:** medical imaging; Laplacian method; image sharpening; X-ray enhancement; cloud computing

## INTRODUCTION

Medical X-Ray imaging plays a critical role in modern healthcare systems, as it supports physicians in diagnosing fractures, pulmonary diseases, and various internal abnormalities. However, the quality of X-Ray images is often constrained by several technical factors, such as low contrast, image noise, and blurred edge structures. These limitations arise from imaging device constraints, radiation exposure settings, and sensor sensitivity, which ultimately reduce the visibility of anatomical structures and may compromise diagnostic accuracy. In radiographic practice, image sharpness is a crucial parameter because unclear object boundaries can hinder medical personnel in identifying abnormalities in bones and soft tissues. Therefore, effective image enhancement techniques are required to improve the visual quality of X-Ray images while preserving essential diagnostic information.

Digital image processing has become one of the most important engineering approaches for enhancing medical image quality and supporting computer-assisted diagnosis systems (Gonzalez & Woods, 2018; Jain, 1989). Among various techniques, image sharpening methods are widely used because they enhance edge information and emphasize object boundaries in grayscale medical images(Burger & Burge, 2016). In particular, the Laplacian method is commonly adopted due to its computational efficiency and its capability to enhance fine image details effectively (Umbaugh, 2017).

Previous studies on medical image enhancement can be grouped into several approaches. The first group focuses on spatial-domain filtering techniques, including histogram equalization, Gaussian filtering, median filtering, and Laplacian sharpening, which are widely applied to improve image visibility and contrast (Castleman, 1996; Russ, 2016). Histogram equalization has been shown to effectively enhance image contrast, while Gaussian and median filters are commonly used as preprocessing steps to reduce noise prior to sharpening operations (Pratt, 2007).

The second group of studies employs numerical and simulation-based approaches to evaluate image enhancement performance using quantitative image quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM) (Sonka et al., 2014). These studies demonstrate that sharpening techniques can significantly improve edge visibility and support better object recognition in radiographic images. In addition, frequency-domain filtering methods have also been explored to enhance image details and reduce artifacts in medical imaging applications (Acharya & Ray, 2005; Parker, 2010).

The third group emphasizes intelligent and optimization-based methods, including machine learning and deep learning approaches for medical image enhancement and restoration (Goodfellow et al., 2016). Convolutional Neural Networks (CNNs) and deep learning-based super-resolution techniques have shown strong performance in improving medical image quality and feature representation (LeCun et al., 2015). However, these methods generally require large datasets, high computational resources, and complex training processes, which can limit their applicability in lightweight or educational environments (Bishop, 2006).

In contrast, classical image processing techniques such as Laplacian filtering remain attractive due to their simplicity, computational efficiency, and ease of implementation, making them suitable for lightweight medical image processing systems (Nixon & Aguado, 2019). Nevertheless, existing studies still provide limited discussion on the practical implementation of Laplacian-based sharpening for X-Ray images using lightweight OpenCV frameworks in cloud-based environments such as Google Colab. This indicates a clear research gap regarding the effectiveness and practical deployment of Laplacian sharpening methods for improving X-Ray image clarity within a simple, accessible, and reproducible computational framework.

This study aims to implement and analyze the Laplacian method for sharpening X-Ray images using digital image processing techniques based on Python and OpenCV. The research specifically focuses on evaluating the capability of the Laplacian method to enhance edge visibility and improve image sharpness in grayscale X-Ray images. In addition, this study evaluates the implementation results through visual analysis of the generated sharpened images and investigates the feasibility of lightweight cloud-based image processing systems for medical imaging applications. The implementation is performed in the Google Colab environment to provide an accessible, lightweight, and reproducible platform for medical image processing research and experimentation (Rosebrock, 2019).

The technical contribution of this study lies in the implementation of a simple and computationally efficient image sharpening framework for medical X-Ray images using the Laplacian method in a cloud-based computational environment. This research is expected to demonstrate that Laplacian-based sharpening can improve image detail visibility and edge clarity while maintaining implementation simplicity and computational efficiency. Furthermore, the study contributes to engineering practice in medical image enhancement by providing a reproducible implementation framework using Python, OpenCV, and Google Colab that can support educational, research, and diagnostic applications. The proposed approach also offers practical advantages for rapid medical image enhancement systems that require low computational complexity and easy deployment in academic or lightweight engineering environments (Szeliski, 2022).

## RESEARCH METHOD

The unit of analysis in this study is digital X-Ray images processed using image sharpening techniques based on the Laplacian method. The analyzed objects consist of grayscale radiographic images containing anatomical structures such as bones and tissue areas that require edge enhancement for better visualization. The study focuses on evaluating the capability of the Laplacian sharpening method to improve image clarity, edge visibility, and detail enhancement in medical X-Ray images. The processing and analysis are conducted using Python programming language and the OpenCV library within the Google Colab cloud computing environment.

This study adopts an experimental engineering research design based on digital image processing implementation. The experimental approach is selected because it allows direct observation of image quality changes before and after the sharpening process. The research design includes several stages, namely image acquisition, image preprocessing, Laplacian filtering implementation, image sharpening, and visual evaluation of the resulting images. The selected design is suitable for addressing the technical objectives of evaluating the effectiveness of the Laplacian method in enhancing X-Ray image sharpness while maintaining computational simplicity and implementation efficiency.

The data sources used in this study consist of digital X-Ray image datasets obtained from publicly available medical image repositories and sample radiographic images used for image processing experiments. The images are stored in digital format such as JPG or PNG and processed as grayscale images to simplify edge enhancement operations. Additional technical references related to image processing algorithms, OpenCV implementation, and medical image enhancement methods are obtained from scientific books, journal articles, and technical documentation. The experimental outputs generated from the implemented algorithm also serve as analytical data for evaluating image sharpening performance.

Data collection in this study is performed through digital image acquisition and computational processing procedures. Initially, X-Ray images are uploaded into the Google Colab environment using file upload utilities. The uploaded images are then read using the OpenCV library and converted into grayscale format to facilitate image processing operations. The Laplacian filtering process is applied to detect intensity transitions and strengthen edge structures within the image. The implementation process utilizes Python programming with OpenCV functions for image reading, filtering, and visualization. The generated sharpened images are subsequently stored and compared visually with the original images to evaluate the enhancement results. The computational environment provided by Google Colab enables reproducible implementation and lightweight processing without requiring dedicated local hardware resources.

The data analysis technique used in this study is based on qualitative visual analysis of image enhancement results. The analysis focuses on evaluating changes in edge visibility, image sharpness, and anatomical detail clarity after applying the Laplacian sharpening method. Comparisons are conducted between original X-Ray images and sharpened images to identify improvements in object boundary definition and structural detail enhancement. In addition, the study evaluates the computational feasibility and implementation efficiency of the proposed method within the Google Colab environment. The engineering analysis also considers the simplicity, reproducibility, and practical applicability of the implemented image sharpening framework for lightweight medical image processing systems.

The research stages implemented in this study consist of image acquisition, grayscale conversion, Laplacian filtering, image sharpening, result visualization, and image storage. The overall process is designed to provide a simple and efficient workflow for improving the visual quality of medical X-Ray images using digital image processing techniques.

## RESULT

The implementation of the Laplacian method for X-Ray image sharpening was successfully conducted using Python programming language with OpenCV libraries in the Google Colab environment. The experimental process consisted of image upload, grayscale conversion, Laplacian filtering, image sharpening, and visualization of the processing results. The input image used in this study was a chest X-Ray image in PNG format, while the output consisted of the Laplacian-filtered image and the sharpened image generated after the enhancement process.

Figure 1 presents the comparison between the original X-Ray image, the Laplacian filtering result, and the sharpened image. The original image shows chest anatomical structures such as ribs, lungs, and surrounding tissue regions. After the Laplacian filtering process, edge structures and intensity transitions became more visible in the image. The Laplacian output primarily highlighted thin edge patterns representing structural boundaries within the radiographic image. Although the filtering result appeared darker than the original image, important edge information was successfully extracted during this stage.

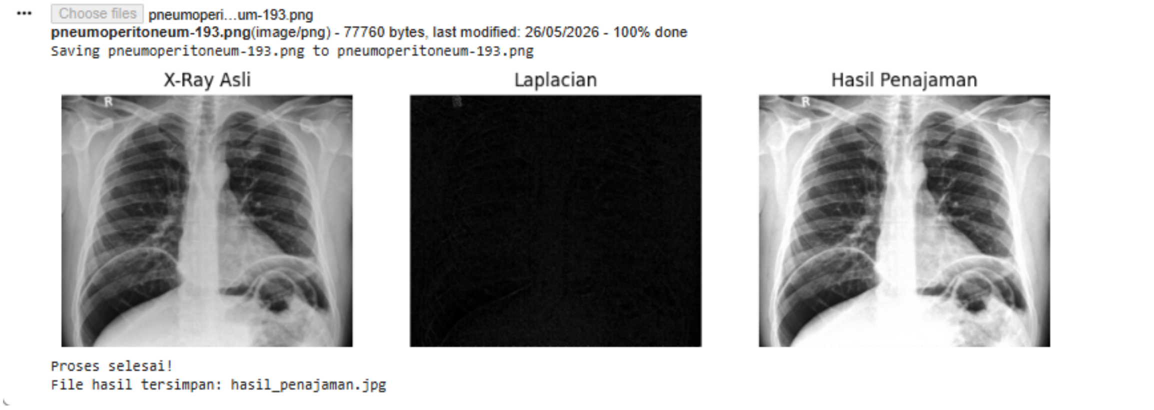


**Figure 1.** Results of X-Ray Image Sharpening Using the Laplacian Method

The sharpening process combined the grayscale image with the extracted Laplacian edge information to improve image sharpness and structural visibility. The resulting sharpened image demonstrated clearer anatomical boundaries compared to the original image. Bone structures, rib edges, and lung regions appeared more distinguishable after the enhancement process. In addition, local contrast around edge regions increased significantly, making structural details easier to observe visually. These findings indicate that the Laplacian method effectively enhanced high-frequency image information associated with edges and fine anatomical details.

The developed system utilized several software components to support the image processing workflow. The implementation framework is presented in Table 1.

**Table 1.** Software and Processing Components Used in the System

| Component | Function |
|---|---|
| Python | Main programming language |
| OpenCV | Image processing operations |
| NumPy | Numerical computation |
| Matplotlib | Image visualization |
| Google Colab | Cloud-based execution environment |

Based on the implementation results, the proposed framework successfully executed all image processing stages efficiently within a lightweight cloud-based environment. The use of OpenCV libraries simplified image processing operations, while Google Colab enabled reproducible experimentation without requiring dedicated local hardware. The processing workflow successfully generated sharpened images automatically and stored the output images in JPG format.

Additional observations regarding the visual characteristics of the processed images are summarized in Table 2.

**Table 2.** Observed Visual Characteristics After Laplacian Sharpening

| Image Component | Observation |
|---|---|
| Rib structures | More clearly defined |
| Lung boundaries | Improved visibility |
| Edge regions | Higher contrast |
| Noise components | Slightly amplified |

The experimental results revealed several dominant visual patterns after the sharpening process. First, anatomical edge structures became significantly clearer compared to the original image. Second, object boundaries within rib and lung regions appeared more prominent due to increased local contrast. Third, fine structural details became easier to identify visually after enhancement. However, the sharpening process also slightly amplified noise components in certain image regions. This condition occurred because the Laplacian operator is highly sensitive to high-frequency information, including both edge structures and image noise.

Overall, the obtained results demonstrate that the Laplacian method can effectively improve X-Ray image sharpness and enhance anatomical detail visibility using a computationally efficient implementation framework. The proposed approach successfully combines lightweight processing performance, implementation simplicity, and practical image enhancement capability for medical image processing applications.

## DISCUSSION

### Summary of Results

The experimental results demonstrated that the Laplacian method successfully improved X-Ray image sharpness and enhanced anatomical boundary visibility. The proposed implementation produced clearer rib structures, lung boundaries, and edge details while maintaining computational simplicity and lightweight processing performance. The

Google Colab-based implementation also enabled accessible and reproducible image processing experiments without requiring specialized hardware.

**Technical Explanation**

The observed image enhancement occurred because the Laplacian operator emphasizes regions with rapid intensity transitions that correspond to object edges and structural boundaries. During the filtering process, high-frequency image components associated with fine details and edges were amplified, resulting in stronger local contrast and improved object visibility. The sharpening operation combined the extracted edge information with the original grayscale image to produce clearer anatomical structures. However, because image noise also contains high-frequency components, the Laplacian operator amplified certain noise regions together with structural edges.

**Comparison with Previous Studies**

The findings obtained in this study are consistent with previous digital image processing studies that reported the effectiveness of Laplacian filtering for edge enhancement and image sharpening applications (Gonzalez & Woods, 2018; Pratt, 2007). Previous research demonstrated that spatial filtering methods are capable of improving medical image visibility by enhancing intensity discontinuities and structural boundaries. Compared with deep learning-based image enhancement methods, the proposed approach offers advantages in terms of computational efficiency, implementation simplicity, and lightweight processing requirements. In addition, the use of Google Colab and OpenCV provides a more accessible implementation framework for educational and small-scale engineering applications.

**Engineering Interpretation**

From an engineering perspective, the results indicate that Laplacian-based sharpening can improve medical image interpretability while maintaining low computational complexity. The enhanced edge visibility may support faster visual observation and improve structural identification in radiographic images. The lightweight implementation framework also demonstrates the feasibility of deploying classical image enhancement techniques in cloud-based environments for educational and rapid prototyping purposes.

### Practical Implications and Engineering Actions

The obtained results provide several practical implications for medical image processing applications. First, the proposed method can be implemented as a lightweight preprocessing stage for enhancing radiographic image visibility before diagnostic interpretation. Second, the use of cloud-based platforms such as Google Colab simplifies implementation and accessibility for researchers, students, and engineering practitioners. Third, future engineering improvements may include integrating noise reduction techniques such as Gaussian filtering before sharpening operations to reduce noise amplification effects. In addition, future studies may incorporate quantitative image quality evaluation metrics and comparative analysis with other image enhancement approaches to improve performance assessment and system optimization.

## CONCLUSION

This study successfully implemented the Laplacian method for X-Ray image sharpening using Python and OpenCV within the Google Colab environment. The experimental results demonstrated that the proposed method effectively enhanced edge visibility, improved anatomical boundary clarity, and strengthened fine structural details in chest X-Ray images. The sharpening process increased local contrast around rib structures, lung boundaries, and other anatomical regions, making important radiographic features more distinguishable compared to the original image. In addition, the implementation process was computationally efficient and capable of operating within a lightweight cloud-based framework without requiring specialized hardware resources.

The findings of this study contribute to engineering knowledge in the field of digital medical image processing by demonstrating that classical edge enhancement techniques remain effective for practical radiographic image enhancement applications. The proposed framework provides a simple, reproducible, and accessible implementation approach using Python, OpenCV, and Google Colab. Compared to more computationally intensive methods such as deep learning-based enhancement techniques, the Laplacian-based approach offers advantages in terms of implementation simplicity, lightweight computation, and ease of deployment for educational and engineering applications.

Therefore, the study contributes both technically and practically to the development of lightweight medical image enhancement systems.

Despite the satisfactory results obtained in this study, several limitations were identified during the experimental process. The Laplacian operator exhibited sensitivity to image noise because both edge structures and noise components contain high-frequency information. As a result, slight noise amplification was observed in several image regions after the sharpening process. Furthermore, the evaluation conducted in this study was primarily based on qualitative visual analysis without incorporating quantitative image quality metrics such as PSNR, MSE, or SSIM. Future research may focus on integrating preprocessing techniques such as Gaussian filtering or noise reduction methods prior to sharpening operations to improve enhancement stability. In addition, future studies may include quantitative performance evaluation and comparative analysis with other image enhancement methods, including deep learning-based approaches, to obtain more comprehensive engineering performance assessments.

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