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An Enhanced Edge Detection Using Laplacian Gaussian Filtering Method from Different Denoising Images

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Abstract: Image processing begins with the phase of edge detection (ED), which comes before the step of identification of objects and is regarded to be the foundation of the processing. This approach includes the process of identifying these spots from images from the viewpoint of the pixels where a quick shift in brightness occurs. Images may be categorized into a wide range of distinct types, including as those utilised in medical, satellite images, articular imaging, industrial imaging, general-purpose imaging, as well as more. By gathering information based on pictures, including the identification and translation of abnormal deflections, the main goal is to enhance clinical diagnosis. In this study, a fresh method for performing image denoising and edge detection preprocessing on various pictures will be given. Different photos will be gathered for this purpose from an internet source, and these will then be preprocessed using filtering techniques. The edges of the images that are entered will first be detected using a Laplacian gaussian filtering technique, after which noise may be removed using a Gaussian filtering strategy. For the purpose of demonstrating the efficacy of the proposed method, nine different photographs, one of which is an x-ray image, will be utilised in the demonstration process. The performance of the suggested edge detection technique will also be evaluated by computing the computational time metrics MSE, RMSE, and PSNR, also calculate execution time. Additionally, to verify the suggested methodology, a comparison with the traditional approaches will be done.

Keywords: *Edge detection, Laplacian of Gaussian, denoising, RMSE, PSNR.*

1. Introduction

The most basic aspect of every image is its edges, which serve as boundaries between various parts and store a plethora of data. When it comes to image processing, ED is a common and crucial technique for detecting and distinguishing geometric forms [1]. In most cases, ED is the method of locating the area of the graph in which the gradient undergoes an important modification and then picking the pixel that has the largest amplitude. Additionally, it can get the edge data of an area by seeking out transfer locations in which the second-order derivative is equal to zero. ED operators typically consist of the Sobel operator, the Laplace operator, as well as the canny operator [2]. Although it is impacted by picture noise, the canny operator is an ED operator that is pretty comprehensive. To enhance the canny operator's ED outcomes, it is crucial to apply suitable filtering (denoising) processing to the picture. This will keep the original edge details intact to the fullest degree while removing noise [3][4][5][6].

Image ED has potential applications in data reduction, segmentation, picture reconstruction, and other well-matched tasks. Making ED is possible in numerous ways. Image differentiation calculation is the gold standard for ED. In a picture, the gradient is used to calculate the first-order variables and the Laplacian to produce the second-order derivatives. The Hilbert Transform is another tool for detecting edges. In addition, we have introduced a novel approach that merges the two methods, namely the short response Hilbert transform (SRHLT). The term "edge detection" is used in the field of image processing to describe techniques that seek to locate picture edges. It shows up in the computer vision domain while working with feature extraction and features election. The output of an edge detector is an edge map, which it generates from a digital picture. Some detectors' edge maps provide direction, strength, and location data about edges [7].

Image denoising techniques abound, including the more conventional median and mean filters as well as more modern Gaussian and other similar algorithms. Denoising is possible with these approaches, albeit at the cost of edge loss, pseudo-edges, and boundary blurring. To avoid the issues that other denoising techniques bring and to eliminate as much noise from the original picture as feasible, this study uses the wavelet transform [8].

1.1. Contribution of the Paper

This research aims to contribute to the area of edge identification using X-ray images of the human. A new method based on the Laplacian of Gaussian (LoG) filtering technique is proposed, along with lowering processing time, improving computing efficiency, and confirming the

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effectiveness of current methods.

- To improve edge detection techniques that use X-rays of the human more efficiently in terms of computing cost.
- Decrease image processing time while maintaining edge detection accuracy.
- A new edge detection method based on the Laplacian of Gaussian (LoG) filtering approach is proposed and evaluated.
- Improving computer vision and image processing by providing a structured approach to strong edge detection even when noise is present.
- To determine the proposed techniques efficiency in terms of RMSE, MSE, PSNR and Execution time.

1.2. Structure of the Paper

For the sections that follow, this study is organised as follows: The comprehensive literature study on ED from denoising images is reviewed in Section 2. In Section 3, the investigation's approach employed to conduct this research project is detailed. Section 4 delves into the outcomes and analysis of the proposed research endeavour. Section 5 contains the results and future intentions of our research investigation.

2. Related Work

Edge detection techniques on different kinds of images have recently attracted a lot of attention from researchers. In what follows, we will go over some relevant research on cutting-edge ED techniques for digital images.

In [9] provide an approach to picture ED that utilises Haar Wavelet transform Modify and evaluate this approach alongside several state-of-the-art ED techniques. Obtaining the image's Y channel is the first step in data preprocessing. Our second step in noise reduction is the use of an adaptive wiener filter. The last step is to perform the Haar Wavelet Transform. After the absolute magnitude image and Otsu Threshold Segmentation processes, we receive the final output picture. After that, it uses the Receiver Operating Characteristic (ROC) curve to assess the results. Our simulation findings show that the suggested ED approach outperforms several state-of-the-art approaches in terms of both clarity and denoising degree.

In this work, [10] Show the edges recovered from both raw and colour photographs using a variety of ED techniques to prove that the raw images are very informative. Because colour and raw photos differ in distribution and properties, we provide CannyRaw, a fast edge recognition method tailored to raw images that does not need any sensor or optics-specific information. Evidence of CannyRaw's resistance to light and noise is shown by the scientific results of edge photos taken at several lighting levels. In addition, removing image signal processing (ISP) can decrease the power and resource requirements of the system.

To achieve the goal, [11] suggest an MLEFGN, or multilayer edge feature guided network. To begin, they take the noisy picture and design an edge reconstruction network (Edge-Net) to make direct predictions of clean edges. The next step is to incorporate the Edge-Net into the model for edge priors, and then use a dual-path network to extract image characteristics and edge features, as appropriate. Our work on image denoising concludes with the introduction of a multilayer edge features guiding system. We believe that Edge-Net is the first convolutional neural network (CNN) model developed specifically for restoring picture edges in the presence of noise; it performs admirably on real-world images and remains stable under pressure. Numerous ablation studies show that our suggested Edge-Net and MLEFGN work and extensive tests show that our MLEFGN outperforms other approaches.

In this work, [12] integrated three effective techniques used in the wavelet domain to enhance denosining quality. In order to handle images in the frequency domain, the discrete wavelet transformation was employed. A combination of the median filter and the soft thresholding approach was used to eliminate noise. In order to maintain the image's sharpness, the denoising technique did not alter the edge coefficients. Using four industry-standard benchmark photos, the suggested technique was evaluated. The suggested technique outperformed the other techniques found in research when comparing the PSNR. The suggested approach effectively removes Gaussian noise, according to the structural similarity index metric.

Accorting to [13] have shown how deep CNN fared compared to standard edge detectors when it came to detecting cracks in concrete constructions using images. After calculating the accuracy of several ED algorithms on 19 HD photos, it was discovered that LOG attained the highest accuracy at 98%, followed by Roberts and Gaussian at 95%.

In [14] created a new approach that utilises a Gaussian filter and statistical range to better identify edges in X-ray pictures taken of humans. In order to improve and preprocess images, a Gaussian filter is employed. On the other hand, for each 3x3 picture matrix split, statistical range is employed to determine the difference between the highest and lowest pixel values. Together, these two can process X-ray pictures for edges. The detection of edges has also been tested on human X-Ray pictures in addition to X-Ray images taken by machines. Additionally, when compared to other methods for edge detection in human X-ray pictures, our suggested solution outperforms the competition in the areas of computation time, PSNR, RMSE, and mean squared error.

In [15] to identify the edge of a CT scan of the lungs using a new mathematical morphological technique. They demonstrated that this technique outperforms common template-based ED methods like the Sobel edge detector and Laplacian of Gaussian (LoG) operator, as well as general morphological ED techniques like morphological gradient operation and dilation residue edge detector when it comes to denoising and edge detecting in medical images.

Table 1. Comparative Analysis of Edge Detection Utilizing Several Algorithms

Ref	Methodology	advantages	challenges	Research gap
Biswas and Hazra [16]	Modified Moore-Neighbor + Range Filtering	Improved edge detection	High computational time	Computational efficiency and speed improvement needed
Romani et al. [17]	RBF Interpolation based Edge Detection	Implemented on X-Ray and standard images, but limited improvement in accuracy and time	Accuracy and computational time not significantly improved	Improved accuracy and computational efficiency
Jianfang et al. [18]	Parallel Otsu-Canny Operator on Hadoop Platform	Reduced running time compared to traditional Canny, especially for large image datasets	Canny operator's performance decreases with increasing image dataset size	Scalability and performance with large image datasets
Kumar et al. [19]	Wideband Spectrum Sensing using CWT and DWT-based Edge Detection	Moving average filtering method, excellent detection accuracy with low signal-to-noise ratio	Failing to account for RF spectrum with actual wireless channel fading and shadowing consequences	Real-world channel effects in wideband spectrum sensing
Alawad et al. [20]	The Use of 16 Fuzzy Templates for Fuzzy Logic-Based ED	Utilizes 16 fuzzy templates for edge shapes	No consideration of image quality parameters, no comparison with other methods	Consideration of image quality parameters, systematic comparison with other methods
Melin et al. [21]	Both Morphological Gradient and Generalised Type-2 Fuzzy Logic may be utilised.	To handle more diverse kinds of images, generalised type-2 fuzzy logic needs some work.	Some image kinds are not good candidates for the defuzzification techniques utilised, such as height and estimate.	Generalized type-2 fuzzy logic improvement, application to various image types
F. Xiaoa et al. [22]	Wavelet-based denoising with thresholding	Effective denoising with BayesShrink and Feature-Adaptive Shrink.	Limited exploration of other thresholding techniques.	Investigation of novel thresholding methods in wavelet denoising.
Sengur et al. [23]	Texture Feature Coding Method (TFCM) based Edge Detection	Novel technique using texture feature coding scheme	Not evaluated against state-of-the-art ED methods; noise in pictures is not taken into account.	Comparison with latest algorithms, robustness to noisy images
Tian et al., [24]	Classic ML and neural network-based models	Effective for parameter estimation on sparse noisy data. Neural networks show improvement with a clearer understanding of	- Challenge in finding optimal hyperparameters. Computationally intensive, particularly with deep neural networks.- Limited	- Explore advanced hyperparameter optimization techniques. Develop computationally efficient neural network architectures for parameter estimation.

		noise forms and network architectures.	interpretability of complex neural network architectures.	Investigate methods for interpreting complex neural network models in the context of sparse noisy data.
Wang et al., [25]	study of DL applications in pore-scale imaging	Comprehensive overview of DL applications in porous media imaging. Identification of common CNN architectures and GANs for image generation.	Brief discussion on image denoising in the review. Limited exploration of specific DL applications in porous media imaging.	Conduct a more in-depth exploration of DL applications in image denoising for porous media. Investigate novel CNN architectures and GANs tailored for specific tasks in porous media imaging.
E. SERT et al. [26]	Neutrosophic Set (NS) Structure with Maximum Norm Entropy	Higher FOM and PSNR results compared to other Neutrosophic Set methods	Noisy images not considered, parameters for comparison not specified	Robustness to noisy images, systematic comparison with latest algorithms

The study of edge detection algorithms has shown that there are a number of significant holes in the current literature. First, improving the computational efficiency and lowering the related high processing time is crucial, even if Modified Moore-Neighbor + Range Filtering showed enhanced edge detection. Furthermore, additional study is needed to increase both the accuracy and computing time of edge detection using RBF Interpolation, as investigated by Romani et al., which has only demonstrated minimal gains. Further research is needed to confirm the claims made by Jianfang et al. on the Parallel Otsu-Canny Operator's performance and scalability on the Hadoop platform. This is especially true when it comes to dealing with massive picture datasets. Alawad et al. suggested 16 Fuzzy Templates for edge identification, although there has not been a thorough investigation of picture quality criteria or systematic comparisons with other approaches in this area. Improvements in computing efficiency, scalability, accuracy, and systematic assessments across different edge detection approaches are necessary to fill these research gaps.

3. Research Methodology

In this section, present proposed approach that we used in this research. It include the methodology part, proposed algorithm and problem statement.

3.1. Problem Statement

In the present state of edge identification in human arm X-ray images, there are limits in terms of the amount of time it takes to analyze the data, the reliability of the results, and the computing performance. There is an opportunity for improvement in the techniques that are currently in use, even after improvements such as modified Moore-Neighbor plus range filtering and RBF interpolation have been included. Furthermore, the assertions that have been made by a variety of research on techniques that include the Parallel Otsu-Canny Operator need confirmation, particularly when dealing with huge datasets, including as those that are used in medical imaging technologies.

3.2. Methodology

We lay out all of the edge-detection techniques that were taken into account in our study here. The suggested method employs a Laplacian of Gaussian (LoG) filtering technique on images devoid of noise in an effort to enhance ED. Starting with several denoising techniques, like Gaussian filtering, the input photographs are made noise-free. The last step in preparing pictures for ED is convolving them using a Gaussian filter once eliminating is complete. This will make the images more uniform. Following that, the picture is passed via the Laplacian filter, which highlights sudden changes in brightness and enables proper edge concentration. The examination of performance study includes performance durations as well as quantitative measurements such as PSNR, RMSE, and MSE. The findings demonstrate that the proposed approach was efficient by revealing a significant decrease in execution time comparing to the baseline procedures. In addition, the MSE and RMSE assessments show fewer imperfections in the image, and the PSNR readings show an overall improvement in the clarity of the image. This comprehensive method has potential uses in computer vision and image processing as it gives a systematic foundation for strong ED even when noise is present. Presented below is a suggested flowchart:

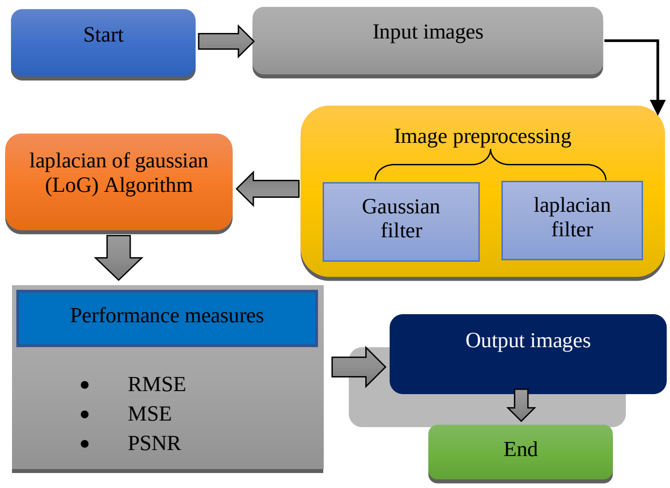

Fig. 1. Proposed algorithm

Fig. 1 depicts the schematic of the suggested approach for identifying borders in X-ray images of humans. You may feed an X-Ray image into this technique. We pre-processed the image because it could have noise, incorrect blurring, or be out of focus. To blur the X-ray picture and eliminate noise and comprehensively, we used a Gaussian filter.

3.2.1. Laplacian filter

The second-order derivative of a picture is computed using a Laplacian filter in digital image processing to identify edges. To improve the feature extraction process, a Laplacian filter is required. We can train an improved model if we can better identify picture characteristics.

3.2.2. Gaussian filter

Blurring the target region and reducing noise at greater amplitudes are two functions of the Gaussian filter. Similarly, to mean filters, it consistently represents average weight. These are linear filters that reduce the noise and blur the edges effectively. They are created as matrices in digital image processing, passing through each pixel of the selected portion.

3.2.3. Denoising

Noise may be defined as a random change in the intensities of pixels that occurs during the process of acquiring digital pictures to be used. Among the various types of noise patterns, speckle noise is produced as a result of random interference between coherent returns, which is caused by variances in the surface of pixels [27]. Synthetic aperture radar pictures, in contrast to optical views, are severely contaminated by speckle noise. Consequently, radar pictures may not be well-served by simple ED algorithms.

3.2.4. Image smoothing

A low-pass filter operation represents essentially what smoothing does. A large portion of the signal strength is concentrated in the low frequency range due to the fact that pictures often display local correlations. As a result, the signal-to-noise ratio (SNR) at low frequencies is higher than at high frequencies after the addition of white noise, which is a flat frequency energy spectrum. By dampening the high-frequency component, image smoothing aims to boost the total signal-to-noise ratio (SNR). In most cases, this enhances SNR throughout, but it significantly blurs high-frequency signal information like edges.

3.3. Proposed laplacian of gaussian (LoG) Algorithm

The LoG is a variant of the Laplacian filter that incorporates a Gaussian filter in addition to the Laplace reacting. Although it outperforms the first derivative variations in identifying tiny edges, the Laplacian is noise-sensitive. Applying a Gaussian filter to a picture before using a Laplacian convolution to identify edges helps minimise the erroneous identification of edges to a minimum. However, the sharp edges may be masked by the smoothing, which could lower the accuracy of edge localization. Hence, the smoothing parameter needs special attention. The most important part of this technique, zero-crossing, is used to accomplish the thresholding [28]. The function that is being convolved with the picture is the two-dimensional Gaussian.

$$G_\sigma(x,y) = e\frac{-(x^2+y_2}{2\sigma^2} \;.....(1)$$

the corresponding Gaussian probability distribution, with σ being its standard deviation [29]. You can apply the Laplacian operator ∇ after the picture has been organised.

$$\nabla^2 = \frac{\delta^2}{\delta x^2} + \frac{\delta^2}{\delta y^2} \;......(2)$$

The Laplacian's invariance to rotation is a benefit as it means it reacts uniformly to modifications in intensity irrespective of the direction of the mask [30]. It is possible to pair the Laplacian operator with the Gaussian filter to get the LoG because the order is irrelevant:

$$\nabla^2 G_\sigma = \left(\frac{r^2-2\sigma^2}{\sigma^4}\right) e^{\left(\frac{-r}{2\sigma^2}\right)} \;.....(3)$$

Where:

$$r = \sqrt{x^2+y^2} \;.......(4)$$

3.4. Edge detection

In computer science, a technique is a complex set of instructions for solving a problem. To extract edges from X-Ray pictures, we have developed an approach that follows these stages.

Algorithm: Edge Detection from X-Ray Images

Step 1: Input an X-Ray Image.

Step 2: Gaussian filter.

Step 3: 3 x 3 partition of an image achieved in step-2

Step 4: Determine the statistical range for each 3 x 3 partition by subtracting the minimum pixel value from the maximum pixel value.

Step 5: Change the pixel value you got in Step 4 with the one in the middle of the 3 X 3 partition.

Step 6: Proceed to iterate through steps 3, 4, and 5 until the final 3X3 image partitions remain.

Step-7: Result utilising Edge Detection.

4. Results & Discussions

In this portion, present the outcome of our analysis for each edge operator presented. This expermetal results perform on Windows 10 machine equipped with an Intel(R) Core (TM) i5-1035G1 processor operating at 1.00 GHz 1.19 GHz, also used python programming tool. It includes the experimental analysis, and evaluation measures.

4.1. Evaluation Measures

To measure the detection performance of the models we looked at, the present research used three main statistical loss functions: RMSE, PSNR, and MSE. Research on time series detection has made heavy use of these loss functions as of late. Below, we will go over the error functions:

4.1.1. Peak Signal to Noise Ratio (PSNR)

One way to quantify the quality of an image's representation is by calculating the PSNR, which is defined as the ratio of the highest feasible signal-to-noise ratio [31]. The decimal scale is used to measure PSNR. Many academics rely on PSNR to determine the quality of an image's reconstruction. In this scenario, the initial data is seen as a signal, but any errors that may occur are seen as noise. An excellent picture quality is indicated by a high maximum PSNR value. Here is one way for expressing the PSNR:

$$PSNR = 10.\log_{10}\frac{(2^n-1)^2}{MSE} \ldots\ldots (5)$$

4.1.2. Mean Square Error (MSE)

For practical purposes, MSE calculates the actual pixel value of typical data with a degraded image [32]. Average squared error between the true picture and the noisy image is the standard formula for calculating MSE. The disparity between the original and damaged images is a good proxy for the inaccuracy. When the value of MSE is low, it indicates that the picture is of excellent quality..

$$MSE = \sum_{M,N}[\mathrm{I1}\,(\mathrm{m,n}) - \mathrm{12}(\mathrm{m,n})]^2 \ldots\ldots 6)$$

4.1.3. Root Mean Square Error (RMSE)

Calculating the square root of the resultant mean value yields the RMSE. Because of its theoretical similarity to statistical models, RMSE is often used to evaluate detection model efficacy [33].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(y_i - y'_i)^2} \ldots\ldots (7)$$

4.2. Experimental Analysis of proposed image with analysis

In this portion, present the result of analysis for the edge detection. Input the original image and filter image with two techniques like gaussian filter, and Laplacian filter. The results are in the form of images.

Fig. 2. Input First X-ray image

```
Execution time: 0.06406021118164062 seconds

Shape of Original Image                    :  (512, 512)
Shape of Laplacian Gaussian Edged Image    :  (512, 512)

MSE score  :   91.12313461303711
RMSE score  :   9.545843839757547
PSNR score  :   28.53451709918358
```

Fig. 3. Final output of First X-ray image

The above figure 2 and 3 shows the output of first input image x-ray dataset. The proposed algorithm obtain MSE of 91.12%, RMSE of 9.54% and PSNE of 28.53%, also model take only 0.065 execution time.

Fig. 4. Input second X-ray image

```
Execution time: 0.05678868293762207 seconds

MSE score  :   70.33750534057617
RMSE score  :   8.386745813518862
PSNR score  :   29.6589339973081
```

Fig. 5. Final output of second X-ray image

The above figure 4 and 5 shows the output of second input image x-ray dataset. The proposed algorithm obtain MSE of 70.33%, RMSE of 8.38% and PSNE of 29.65%, also model take only 0.056 execution time.

Fig. 6. Input third X-ray image

```
Execution time: 0.06539106369018555 seconds

MSE score :  69.1275863647461
RMSE score :  8.314300112742268
PSNR score :  29.734289673989252
```

Fig. 7. Final output of third X-ray image

The above figure 6 and 7 shows the output of third input image x-ray dataset. The proposed algorithm obtain MSE of 69.12%, RMSE of 8.31% and PSNE of 29.73%, also model take only 69.12 execution time.

Fig. 8. Input fourth X-ray image

```
Execution time: 0.05541062355041504 seconds

MSE score :  52.50944519042969
RMSE score :  7.2463401238438765
PSNR score :  30.928429312688714
```

Fig. 9. Final output of fourth X-ray image

The above figure 8 and 9 shows the output of fourth input image x-ray dataset. The proposed algorithm obtain MSE of 52.50%, RMSE of 7.24% and PSNE of 30.92%, also model take only 0.055 execution time.

Fig. 10. Input fifth X-ray image

```
Execution time: 0.06487178802490234 seconds

MSE score :  29.205097198486328
RMSE score :  5.4041740533116
PSNR score :  33.476217048994215
```

Fig. 11. Final output of fifth X-ray image

The above figure 10 and 11 shows the output of fifth input image x-ray dataset. The proposed algorithm obtain MSE of 29.20%, RMSE of 5.40% and PSNE of 33.47%, also model take only 0.064 execution time

Fig. 12. Input sixth image

```
Execution time: 0.06914830207824707 seconds

MSE score :  107.93115615844727
RMSE score :  10.388992066531154
PSNR score :  27.799335316202708
```

Fig. 13. Final output of sixth image

The above figure 12 and 13 shows the output of sixth input image x-ray dataset. The proposed algorithm obtain MSE of 107.93%, RMSE of 10.38% and PSNE of 27.799%, also model take only 0.069 execution time

Fig. 14. Input seventh image

```
Execution time: 0.06420445442199707 seconds

MSE score :  105.86118698120117
RMSE score :  10.288886576360008
PSNR score :  27.88343601606618
```

Fig. 15. Final output of seventh image

The above figure 14 and 15 shows the output of seventh input image x-ray dataset. The proposed algorithm obtain MSE of 105.86%, RMSE of 10.28% and PSNE of 27.88%, also model take only 0.064 execution time

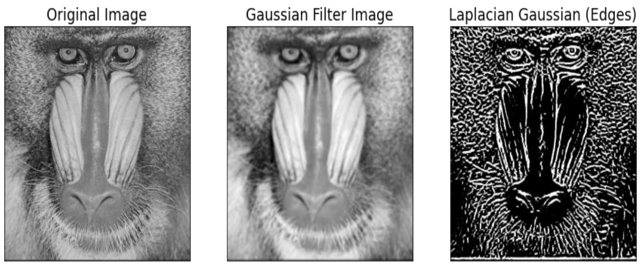

Fig. 16. Input eight image

```
Execution time: 0.0477442741394043 seconds
```

```
MSE score :  103.19231033325195
RMSE score :  10.158361596894055
PSNR score :  27.994330250521283
```

Fig. 17. Final output of eight image

The above figure 16 and 17 shows the output of eight input image x-ray dataset. The proposed algorithm obtain MSE of 103.19%, RMSE of 10.15% and PSNE of 27.99%, also model take only 0.04 execution time.

Fig. 18. Input nine image

```
Execution time: 0.05964326858520508 seconds
```

```
MSE score :  105.76191711425781
RMSE score :  10.284061314201594
PSNR score :  27.887510463303805
```

Fig. 19. Final output of nine image

The above figure 18 and 19 shows the output of nine input image x-ray dataset. The proposed algorithm obtain MSE of 103.76%, RMSE of 10.28% and PSNE of 27.88%, also model take only 0.04 execution time.

For edge detection, imput images and preprocess the image with gaussian filter and Laplacian filter. The abovementioned figures shows the exeution time and evaluation measures including RMSE, MSE, and PSNR.

4.3. Comparative analysis

In this part, describe the comparative analysis of proposed and base images. The comparison of analysis is the form of graphs and tables.

Table 1. Comparison of execution time of base and propose images

Input Image	Base Execution Time	Proposed Execution Time
1	5.0	0.06
2	4.9	0.05
3	4.4	0.06
4	4.5	0.05
5	4.0	0.06
6	4.6	0.06
7	5.0	0.06
8	4.8	0.04
9	4.8	0.05

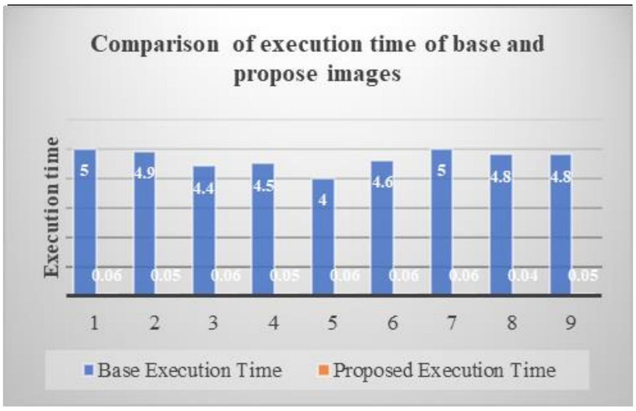

Fig. 20. Comapritive grapg of execution time of images

The above figure 20 and table shows the comparison of execution time of base and propose images. In terms of image quality, the proposed strategy improves the baseline algorithm by lowering mistakes and inconsistencies, as shown by the execution time comparisons. The proposed model take very minimum time in compare to base models.

Table 2. Comparison of MSE, RMSE of base and propose images

Input image	Base images		Proposed images	
	RMSE	MSE	RMSE	MSE
1	8388.11	91.1	91.5	9.54
2	6176.46	70.3	78.5	8.38
3	5070.63	69.1	71.2	8.31
4	4826.02	52.5	69.4	7.24
5	4052.60	29.2	63.6	5.40
6	19736.37	107.9	140.4	10.3
7	17651.49	105.8	132.8	10.2
8	18553.14	103.1	136.2	10.1
9	17746.18	105.7	133.2	10.2

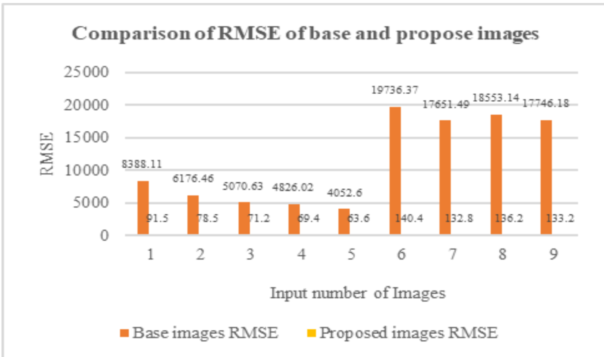

Fig. 21. Comapritive graph of RMSE of images

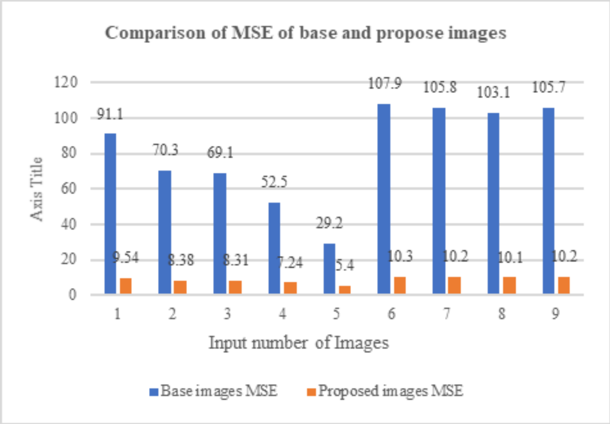

Table 22. Comapritive graph of MSE of images

The above figure 21, 22 and table 2 shows Comapritive graph of RMSE, MSE of propose and base images. MSE and RMSE comparisons reveal that the proposed algorithm outperforms the base algorithm in terms of image quality, reducing errors and discrepancies.

Table 3. Comparison of PSNR of base and propose images

Input Image	Base PSNR	Proposed PSNR
1	8.89	28.5
2	10.2	29.6
3	11.0	29.7
4	11.2	30.9
5	12.0	33.4
6	5.1	27.7
7	5.6	27.8
8	5.4	27.9
9	5.6	27.8

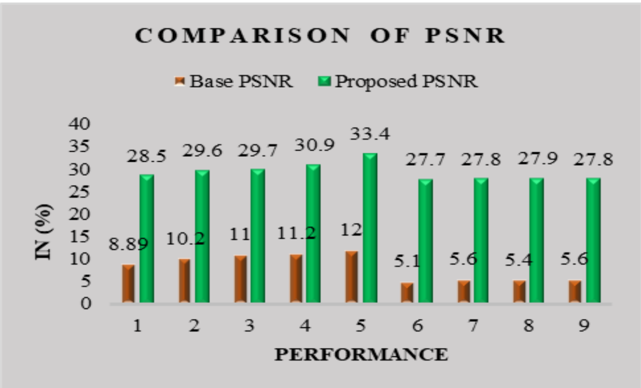

Table 23. Comapritive grapg of PSNR of images

The above figure 23 and table 3 shows comapritive graph of PSNR of propose and base images. In addition to showing improved edge detection capabilities, the proposed methods outperforms the base algorithm in terms of PSNR metrics. For applications requiring precise and efficient edge detection in the presence of image noise, it represents a highly promising solution.

5. Discussion

A critical evaluation of the efficacy of the image processing techniques is achieved through a comparative analysis of the suggested methods and base images, taking into account performance metrics including RMSE,MSE, PSNR, as well as execution time.

The proposed image processing method routinely outperforms the baseline method in terms of execution time and substantially decreases processing times throughout the board (as shown in Table 2). For instance, the basic execution timings range from 4.0 to 5.0 seconds, whereas the proposed method yields substantially reduced timings, between 0.04 and 0.06 seconds.

There is a significant enhancement in the areas of MSE and RMSE when comparing the basic approach to the recommended strategy, as seen in Table 3. Compared to the original base image's MSE of 29.2 in the original, the proposed picture achieves a lower value of 5.40 in the fifth image. The RMSE for the base image was 4052.60, whereas the proposed image had a reduced value of 5.40. These reduced RMSE and MSE values demonstrate greater image integrity and less errors.

In table 4 present the comparative analysis of PSNR valus of base and propose images. We can see the propose images PSNR value higher than comparative to other base images. It represent the PSNR value range of 27.7 to 33.4. the proposed approach prove that has significantly enhace the quality of each images comparaed to base images.

Findings show that the proposed approach of processing images finds an impeccable balance between minimal computational burden and excellent picture quality. For image processing jobs where accuracy and speed are paramount, the suggested method is superior to the baseline method in all three metrics. The picture's properties and the application's needs dictate the precise parameter values that produce these outcomes.

6. Conclusion and Future Work

In this research, used X-ray images of the human arm to show that a Gaussian filter and statistical range method for edge detection is successful. To improve the signal-to-noise ratio, our suggested technique uses a Gaussian filter to lower the noise level and another filter to smooth the picture. The LoG strategy is a smart new way to find edges. The LoG optimizes edge recognition and decreases noise by combining the best features of the Laplacian and Gaussian filters. We convey a method for finding edges in X-ray images by iteratively substituting pixel values and using Gaussian filtering. The results of the trials validate our approach. The table and graph make it easy to compare our method's execution time to that of the fundamental methodology. Our approach significantly shortens runtimes. The proposed approach also consistently outperforms the foundational technique on image quality metrics. There is a considerable reduction in distortion, as shown by measurements for MSE and RMSE, and an increase in image quality metrics like PSNR. These results show that our technique works and is efficient, which is good news for computer vision and image processing systems that need reliable and accurate edge recognition, even with noisy pictures. In order to improve the image quality and decrease noise, we can develop a new filter that bypasses the constraint in future work.

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