Low-Complexity Convolutional Neural Network for Salt and Pepper Noise Removal in Digital Images

IV B.Tech Final Project Review

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INTRODUCTION TO IMAGE DENOISING

- Digital Images are get affected by Salt and pepper noise (SPN) and AWGN due to noisy camera sensors, imperfect transmission, and storage.
- Image denoising plays a crucial role in numerous applications, including medical imaging, surveillance, photography, and satellite imagery.
- High-quality images are essential for accurate diagnosis in medical imaging, reliable monitoring in surveillance, and stunning visual output in photography.
- Existing denoising methods often fall short in effectively removing noise while preserving important image details, highlighting the need for innovative approaches.

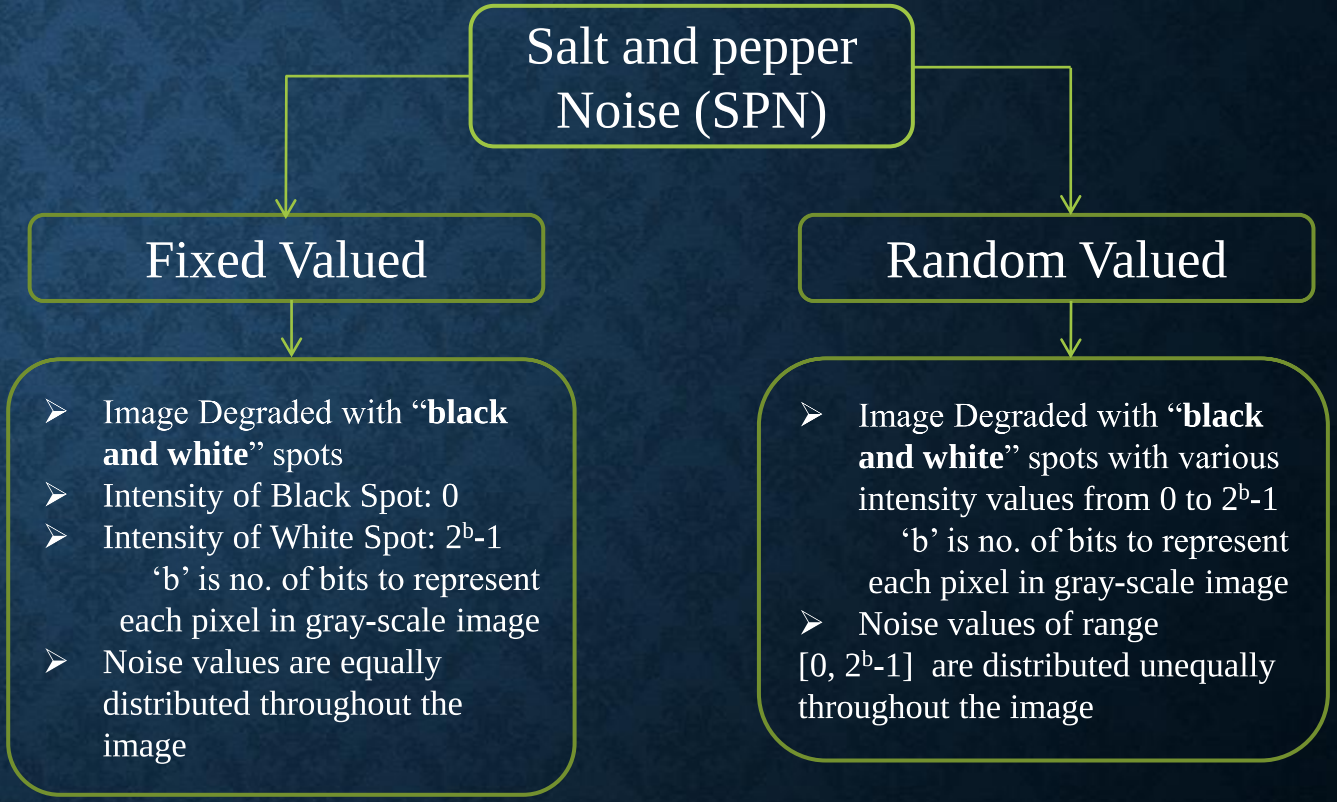

Figure 1: Classification of Salt and pepper

INTRODUCTION TO RCNN

- The Residual Convolutional Neural Network (RCNN) emerges as a novel approach to image denoising, leveraging deep learning techniques to achieve superior noise reduction performance.
- RCNN addresses the limitations of traditional denoising methods by employing advanced neural network architectures and optimization algorithms to deliver clearer, more visually appealing images with reduced noise levels.
- RCNN utilizes residual learning and skip connections to overcome challenges like gradient vanishing and explosion during training.
- The network architecture is designed to learn the residual information directly, leading to improved denoising performance compared to conventional methods.

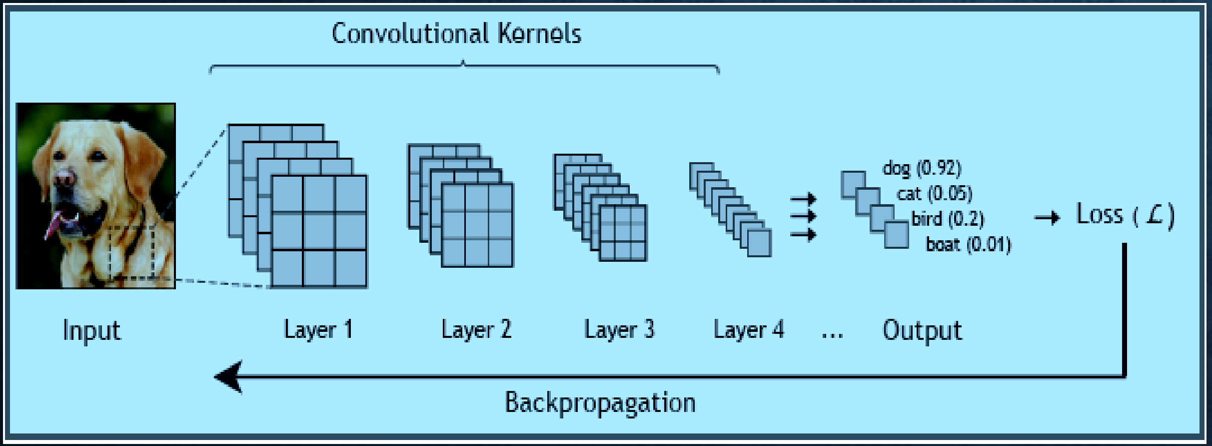

Figure 2: Schematic view of a convolutional neural network for an image classification task

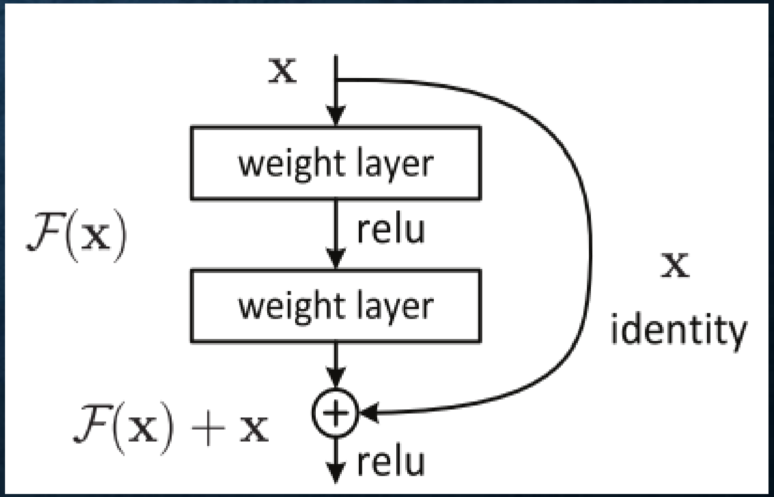

Figure 3: Residual Block

LITERATURE REVIEW

- Traditional Approaches:
  - Techniques like Gaussian smoothing, median filtering, and Wiener filtering have been widely used for denoising. These methods are based on mathematical models and heuristics to remove noise from images.
  - Example:

    Gaussian smoothing applies a convolution kernel to the image to blur out noise. However, it can lead to loss of image details. Wiener filtering aims to minimize the mean square error between the estimated and original image but requires knowledge of noise statistics. [3], [4], [6].

- Deep Learning Approaches:
  - Recent advancements in deep learning have led to the development of convolutional neural networks (CNNs) specifically designed for image denoising. Methods like DnCNN (Deep Convolutional Neural Network) and RCNN (Residual Convolutional Neural Network) have demonstrated significant improvements in denoising performance.
  - Example:

    DnCNN uses a deep CNN architecture with residual learning to directly learn the mapping between noisy and clean images. RCNN, introduced in this study, extends the concept of residual learning with skip connections to enhance denoising performance. [9], [10].

PROBLEM STATEMENT

- Challenges in image denoising:
  - Noise Removal: Existing denoising methods often struggle to effectively remove noise while preserving important image details.
  - Kernel Estimation: Accurately estimating the noise distribution and characteristics poses a significant challenge for traditional denoising techniques.
- Limitations of current methods:
  - Traditional Methods: Conventional denoising techniques such as median filtering or Gaussian blurring may result in loss of image sharpness or detail.
  - Deep Learning Approaches: While deep learning-based methods have shown promise, they may suffer from issues like overfitting or lack of generalization to diverse noise types and levels.
- Justification for Exploring RCNN:
  - Overcoming Conventional Constraints: RCNN offers a novel approach by leveraging deep neural networks with residual learning and skip connections to address the limitations of traditional denoising methods.
  - Potential for Improved Performance: The inherent architecture of RCNN enables it to learn complex noise patterns and enhance denoising performance, making it a promising solution for overcoming existing challenges in image denoising.

NEED FOR ADVANCED DENOISING TECHNIQUES

- Increasing Demand for High-Quality Images:
  - Images play a crucial role in decision-making across various fields.
  - Noise in images can hinder accurate analysis and interpretation.
- Limitations of Existing Methods:
  - Traditional techniques often blur important details along with noise.
  - Advanced methods require precise noise characterization, limiting their applicability.
  - There's a need for techniques that can effectively remove noise while preserving image features.
- Role of Advanced Denoising Techniques:
  - Deep learning-based approaches offer promising solutions by learning complex noise patterns.
  - They can distinguish noise from actual features, leading to more accurate denoising. These techniques leverage large datasets and computational resources for superior performance.

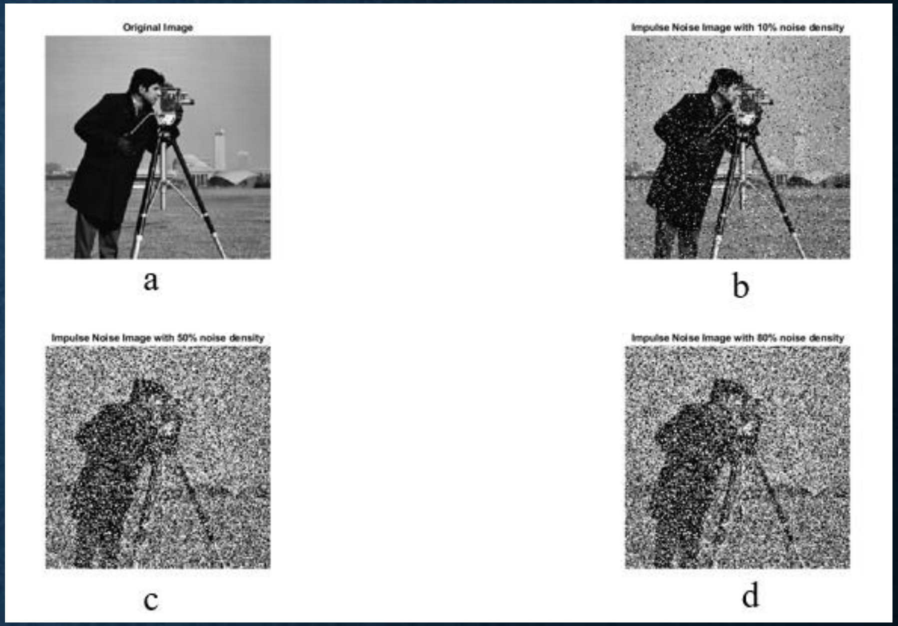

Figure 4: (a) Cameraman Image of size 256 x 256
(b) Salt and pepper noise image (10% noise density)
(c) Salt and pepper noise image (50% noise density)
(d) Salt and pepper noise image (80% noise density)

OPTIMIZERS

- Residual Network (ResNet):
  - Introduced after AlexNet's success in LSVRC2012.
  - Addresses the challenge of training deep networks with hundreds or thousands of layers while maintaining performance.
  - Enhances performance in various computer vision tasks beyond image classification.
- Revisiting ResNet:
  - Introduces identity shortcut connections to address the vanishing gradient problem.
- ResNet revolutionized deep learning by enabling the training of very deep networks.
- Recent variants and interpretations of ResNet further enhance its performance and efficiency.
- Object detection algorithms and optimization techniques continue to evolve, aiming for faster processing and improved accuracy.

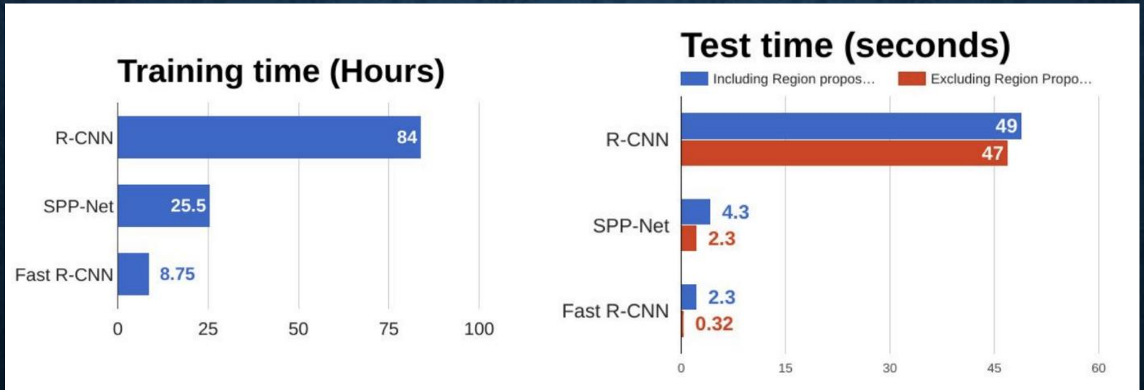

Figure 5: Comparison of object detection algorithms

PROPOSED METHOD

- Introduction to RCNN architecture:
  - Utilizes residual learning and skip connections to address challenges in deep network training.
  - A three-stage architecture consisting of convolutional layers, batch normalization, and transpose convolution layers.
- Components of RCNN:
  - Residual learning: Helps in mitigating the vanishing gradient problem, enabling training of deeper networks.
  - Skip connections: Allow for the reuse of earlier layer activations, facilitating better gradient flow and training efficiency.

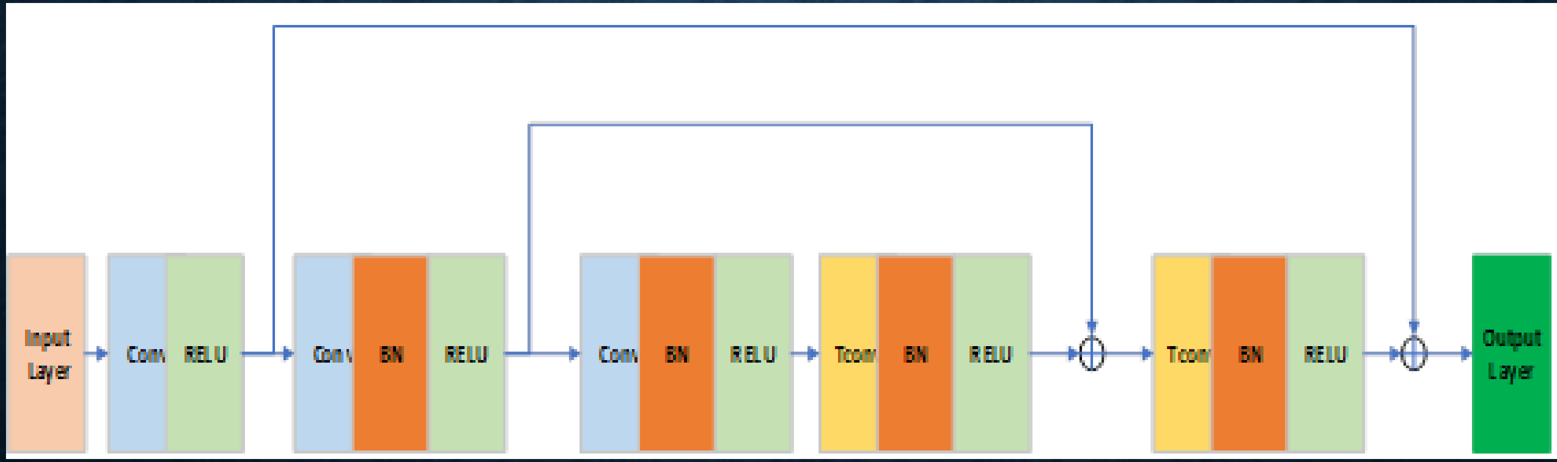

Figure 6: : Proposed RCNN architecture for Image deconvolution

PROPOSED METHOD CONTD..

- Explanation of Adam's optimizer:
  - Adaptive learning rate optimization algorithm used for training the RCNN model.
  - Calculates individual learning rates for different parameters based on estimates of first and second moments of gradients.
  - It helps in optimizing the weights of the neural network by minimizing the loss function efficiently.
- Training Process Details:
  - Dataset: Utilized a dataset comprising 12 images for training.
  - Noise Level: Applied a noise level of $\sigma = 50$ during training.
  - Number of Epochs: Trained the RCNN model for 30 epochs.
- Overview of RCNN Implementation in MATLAB:
  - Implemented the proposed RCNN architecture using MATLAB's deep learning toolbox.
  - Training Time: Approximately 21 hours on a CPU.
  - Utilized Adam's optimizer for optimization during training.

RESULTS AND DISCUSSION

- Simulation Results:
  - Demonstrated the effectiveness of RCNN through simulation results.
  - Trained the RCNN network with a dataset of 400 images from the Berkeley Segmentation Dataset (BSD) for 30 epochs using Adam's optimizer and tested with the set of 12 standard images.
- Comparative Analysis:
  - Compared denoising performance with existing methods such as deconvolution.
  - Highlighted the superior performance of RCNN in terms of PSNR and SSIM values.

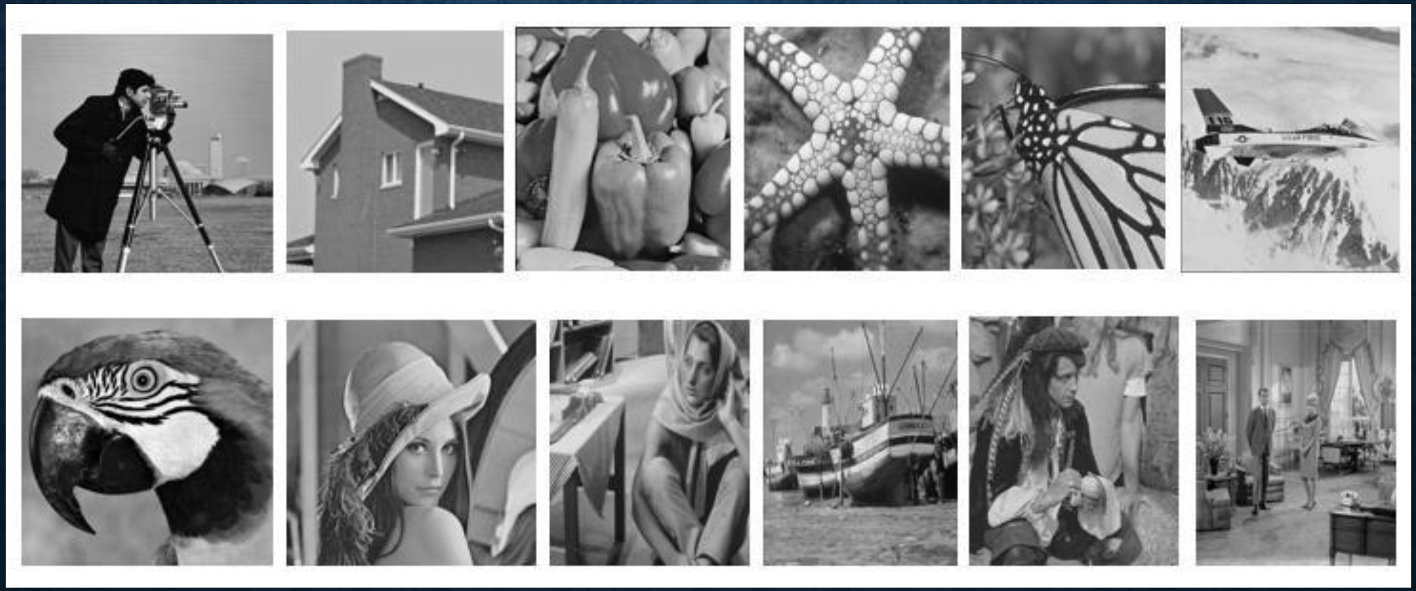

Figure 7: Data Set of 12 images

RESULTS AND DISCUSSION CONTD

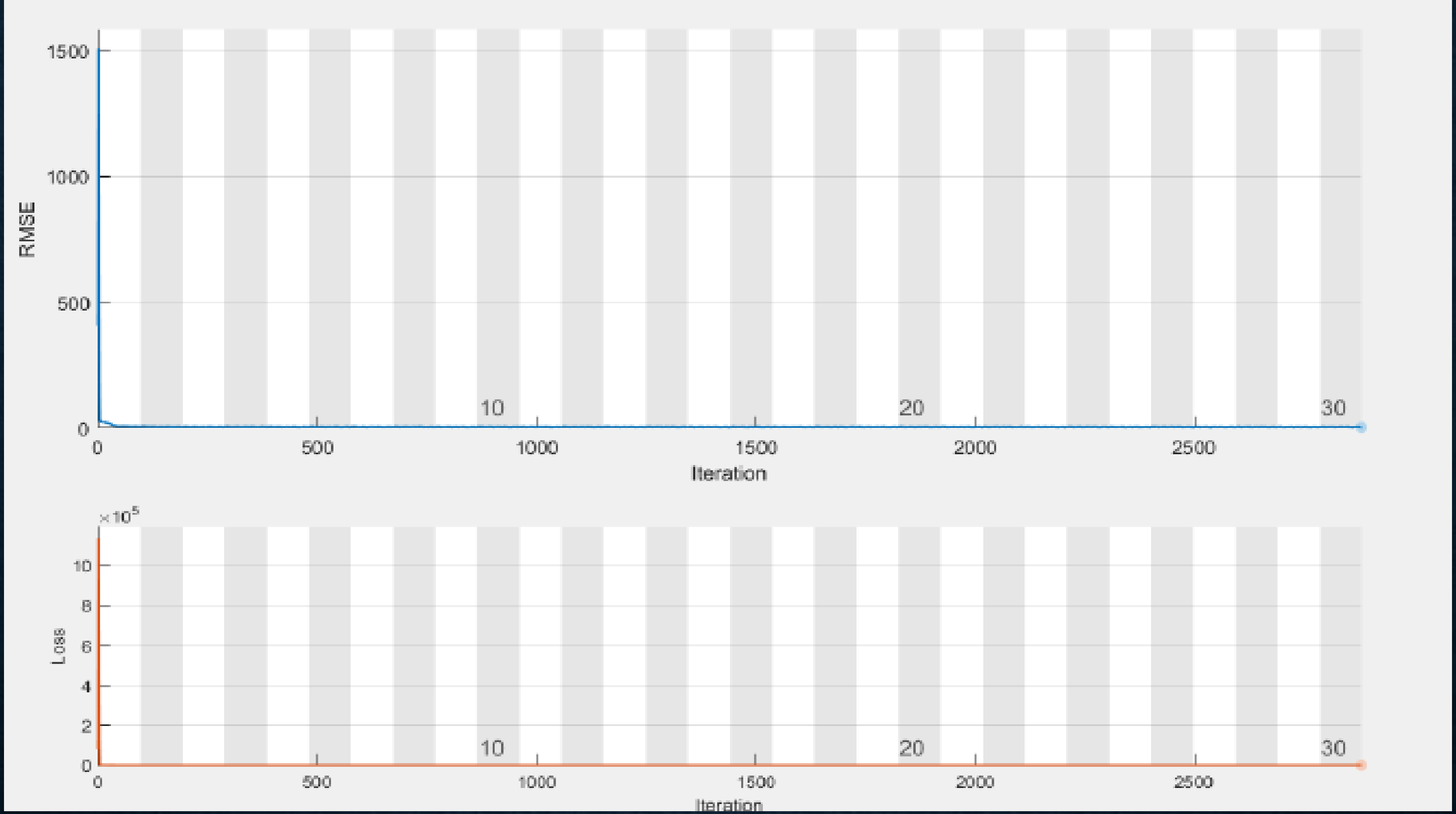

Figure 8: RMSE and LOSS curve of training

RESULTS AND DISCUSSION

- Visualization of Denoising Results:
  - Presented denoising results using sample images to illustrate the effectiveness of RCNN.
  - Showcased visually clear images obtained after denoising with RCNN compared to noisy input images

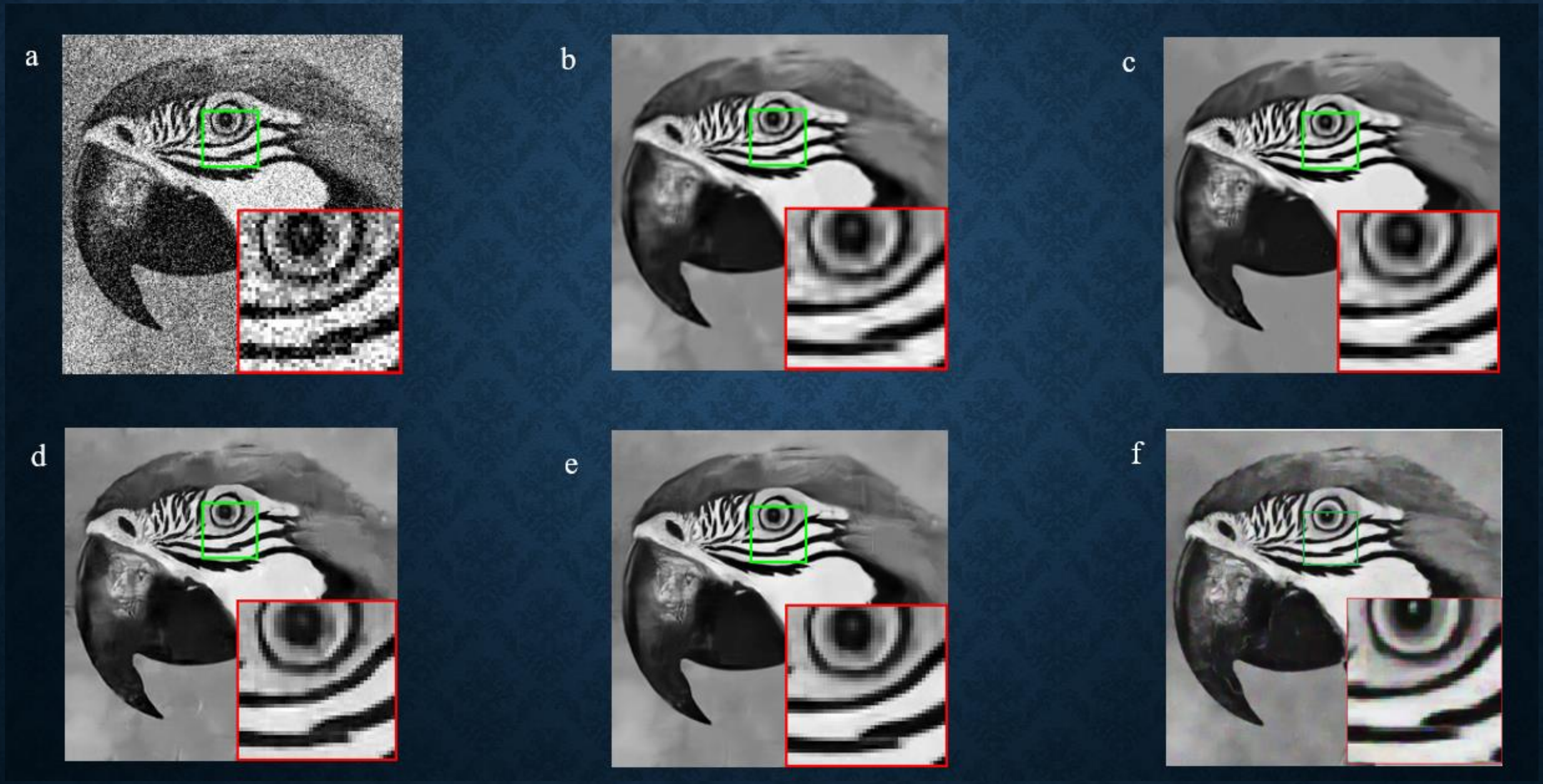

Figure 9: a - Noisy Parrot Image with 50% noise, b - PSNR: 25.8 dB [10], c - PSNR: 26.1 dB [11], d - PSNR: 25.9 dB [12], e - PSNR: 26.4 dB [13], f - PSNR: 27.2 dB Proposed

RESULTS

Table 1: PSNR comparison of DnCNN and RCNN for the data set of 12 images

Image	PSNR DnCNN (dB)	PSNR Proposed (dB)	SSIM DnCNN (dB)	SSIM Proposed
1	20.43	22.76	0.89	0.88
2	21.63	23.41	0.87	0.89
3	21.00	23.04	0.84	0.86
4	20.79	22.80	0.91	0.92
5	21.28	23.34	0.88	0.85
6	21.01	23.00	0.86	0.91
7	21.09	27.20	0.87	0.92
8	21.78	23.34	0.85	0.84
9	20.46	22.24	0.92	0.91
10	21.00	23.01	0.84	0.86
11	21.46	22.95	0.85	0.88
12	21.03	22.88	0.86	0.90

$$MSE = \frac{1}{MN}\sum_{n=0}^{M}\sum_{m=1}^{N}[\hat{g}(n,m) - g(n,m)]^2$$

$$PSNR = 10\ log(255\text{^}2/MSE)$$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)}$$

CONCLUSION

- Key Findings Recap:
  - Emphasized the effectiveness of RCNN in image denoising based on the study's findings.
  - Highlighted the significant improvement in denoising performance achieved with RCNN compared to existing methods.
- Summary of Conclusions:
  - Proposed RCNN demonstrated superior performance in image denoising compared to traditional and deep learning based methods.
  - Concluded that RCNN, with its innovative architecture and training approach, offers a promising solution for challenging denoising tasks.
- Future Research Directions:
  - Suggested exploring RCNN in other image processing tasks or datasets to further validate its effectiveness and versatility.
  - Highlighted potential applications of RCNN beyond denoising, indicating its potential in various domains such as medical imaging, surveillance, and remote sensing.

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Thank You