**Journal of Information Systems Engineering and Management**
2025, 10(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

# An Enhanced Model for Mammogram Image Denoising Using a CNN Autoencoder with Residual Connections

Priyanka Gupta[1], Ramandeep Sandhu[2]

*[1,2] School of Computer Science & Engineering*

*[1,2] Lovely Professional University, Punjab*

*[1]priyankaquick@gmail.com*

*[2]ramandeepsandhu887@gmail.com*

**ARTICLE INFO**

Received: 02 Oct 2024
Revised: 02 Dec 2024
Accepted: 15 Dec 2024

**ABSTRACT**

Image denoising has a wide range of applications in obtaining better-quality noisy data, such as medical imaging and low-light photography. This work proposes a new CNN autoencoder architecture also equipped with a residual connection that advances state-of-the-art performance on this denoising benchmark. The proposed model is compared with state-of-the-art methods, including conditional GAN, CNNs with advanced loss functions, and self-supervised learning models in terms of PSNR, SSIM, and computational loss. It achieves the best results on metrics of PSNR at 44.82, SSIM at 0.970, and a loss value as low as 0.015 on a custom dataset of medical images. These results reveal the efficiency of the architecture in noise reduction while retaining the critical information about the structure and, hence, have many promises in real-world applications. The emphasis here is on an application of residual connections fused with deep learning models having superior state-of-the-art performance in image denoising.

**Keywords:** Denoising, CNN, PSNR, SSIM, Mammogram, Cancer.

## Introduction

Image denoising is one of the major issues in both digital image processing and computer vision. In the process of denoising, quality improvement of the image enables it to be used for further analysis and different applications in medical imaging, remote sensing, and low-light photography. The key issue of image denoising mainly consists of removing possible noise introduced in the acquisition, transmission, or storage while preserving important structural integrity and high frequency details of the original image. Over the last couple of years, deep learning-based techniques, especially Convolutional Neural Networks, have emerged as the state-of-the-art for this task since they have the capability to learn complex noise distributions and hierarchical features directly from data [1][2].

Traditional denoising methods, including median filtering, wavelet thresholding, and non-local means, are based on predefined assumptions about noise characteristics and image properties. Whereas such methods are usually computationally efficient, they typically have shortcomings regarding real diverse and complex kinds of noise, especially in natural scenes. For example, they may blur edges or fail to distinguish noise from fine structural details, which leads to the loss of usefulness of the denoised images in downstream tasks [3], [4]. Over the last few years, CNN-based autoencoders have indeed shown strong promise for overcoming some challenges associated with image denoising. Autoencoders, due to their encoder-decoder architecture, are really suited to learn compact representations of input data while reconstructing the input originally at the output layer. These models are usually trained to map noisy images to clean images when applied for denoising, hence finding and removing the noise artifacts. The variants, such as CDAE, have recently been equipped with state-of-the-art features that include skip connections, residual learning, and attention mechanisms, boosting the performance and efficiency in denoisingactallogoty [5], [6]. Improvements in denoising methods have benefited medical imaging, where noise-free images are of primary importance for diagnosis and treatment planning. The presence of noise in a medical image may mask its diagnostic features and can even lead to false diagnosis. In fact, one can achieve impressive noise reduction with the preservation of clinically relevant details by incorporating denoising autoencoders. These enhance the diagnostic algorithm accuracies and radiologist assessments by improving the signal-to-noise ratios without the loss of clinically useful information 7. For instance, recent research has demonstrated that CNN-based autoencoders have great success in pre-processing medical images, removing Gaussian and Poisson noise with a large margin of increased PSNR and SSIM metrics [].

Traditional pre-processing methods, such as wavelet-based denoising, in combination with deep learning models provide a hybrid approach that houses strength from both paradigms. For example, traditional methods may serve as a strong initialization step in noise reduction to which the deep learning models will further refine and fine-tune. This hybrid approach, especially in medical imaging, has enjoyed great success with most of the pre-processing steps using median filtering and wavelet transforms to deal with artifacts and noise patterns before the application of a machine learning model. The idea of the generalization of noise patterns in training is at the center of denoising autoencoders and is what enables it to denoise images previously unseen. It essentially compresses the input image into a latent representation by extracting from it all the important features, while the decoder reconstructs the clean image from this representation. The advances within the CNN architecture, combined with the addition of dilated convolutions, attention mechanisms, and batch normalization, have additionally made these denoising models robust and scalable. Attention-guided networks, for example, give preference to image regions with a high level of noise, hence allowing for more effective and selective denoising [4]. Besides, residual learning together with skip connections enhance preservations of high-frequency details such as edges and textures that are crucial for maintaining the visual quality and interpretability of the denoised images [7].

On this note of view, the CNN-based autoencoder is similar to traditional denoising techniques with very sound computational advantages, at least for large-scale and high-dimensional data. The parallel processing capability provided by modern GPUs along with the well-optimized architecture of CNNs enabled real-time denoising, which in turn is critical for autonomous vehicles, surveillance systems, or live video streaming. Moreover, the CNN-based schemes can be easily fine-tuned to multiple levels and types of noise by training on various datasets, hence making them extremely versatile and suitable for any general imaging scenario. Recent works have also interpreted and made the process of denoising autoencoders more robust. For example, self-supervised learning paradigms and diffusion-based models have been adopted to enhance generalization capabilities for denoising networks when large annotated datasets are not required. These leverage inherent structure in the data to guide learning, thereby attaining state-of-the-art performance across a broad set of noise types and intensities [2], [5]. Considering CNN-based autoencoders in image denoising is an important departure from traditional methods in that it focuses on learning from the data in an end-to-end fashion. This would further extend beyond the current advances in model architecture and training strategies, possibly also with hybrid approaches. The work presented here looks into the implementation of a CNN-based autoencoder with residual connections for the preprocessing and denoising of noisy medical images. The proposed approach will employ a smart fusion of the traditional preprocessing methods with deep learning methods for offering a robust noise reduction and high-quality reconstruction of an image, opening a way towards improved diagnosis and analysis in medical domains.

## Related Work

The authors in [10] proposed a method for learning robust classifiers using Denoising Masked Autoencoders (DMAE). DMAE injects noise into image pixels and masks patches during training while leveraging a transformer-based encoder-decoder model for reconstructing clean images. The applications of this model to various datasets such as ImageNet and CIFAR-10 have led to large gains in terms of classification accuracy and outperformed state-of-the-art methods on many robust classification tasks. The parameter efficiency and ease with which it generalizes to a wide variety of downstream tasks will likely make it of much value for image denoising and beyond. The authors, in, developed the performance analogy of the autoencoders for image denoising by comparing several autoencoder architectures: Basic, Denoising, and Convolutional Autoencoders. They showed that Convolutional Denoising Autoencoders outperform the other architectures when it comes to the quality of the reconstructed images. Such results provide insight into the strengths and weaknesses of each architecture, enabling one to choose the right autoencoder in a practical scenario.

In, a novel approach of Fourier Autoencoder Model was proposed for image deblurring. A new model was presented, integrating a CNN model with a Fourier transform to remove motion blur for better clarity in an image. The system performed exceptionally well by deblurring using two autoencoders: one for extracting features and another for optimization. Detailed experiments were developed to validate its effectiveness, especially preserving more image details, reducing computational complexity, and having potential real-time applications.

In the work [13], the authors have dealt with Image Denoising Using Convolutional Neural Networks, wherein their concentration is on noisy medical images. A novel deep autoencoder network proposed effectively suppresses noise artifacts without necessarily performing large sets of datasets. The proposed model has excellent denoising performance for medical images of diverse heterogeneity, yielding high PSNR values. This shows that network architectures even with a simplified version generate considerable denoising performance, thus less computational for clinical usage.

The authors of [14] proposed an Advanced Image Deblurring Framework by introducing a specially designed hidden layer combined with autoencoders. The model was optimized in terms of encoder and decoder networks, which helps to capture critical image details and sharpness. Extensive experiments show improvements of PSNR and SSIM scores with sharper reconstructed images compared to traditional approaches. This framework has marked the effectiveness of deep learning on challenging tasks such as image deblurring and denoising.

Table I Literature Reviw

| **Citation** | **Dataset and Learning Model Used** | **Results** | **Outcome** |
|---|---|---|---|
| [15] | MNIST dataset, CNN combined with Non-Local Self-Similarity based denoising methods (NSS-UNet). | PSNR: 33.8 dB, SSIM: 0.92 | NSS-UNet outperformed standard CNN and NSS models for repetitive structure image denoising. |
| [16] | Breast histopathology images, Variational Autoencoder (VAE) and Denoising Variational Autoencoder (DVAE). | Accuracy: 73% | DVAE produced better cancer detection rates compared to baseline CNNs. |
| [17] | Fashion MNIST dataset, Autoencoder with redundancy-reduction bottleneck loss. | PSNR: 32.5 dB, SSIM: 0.89 | Improved representation diversity and reconstruction accuracy over standard autoencoders. |
| [18] | Custom hyperspectral X-ray dataset, Convolutional Autoencoder compared to Wiener filter. | PSNR close to Wiener filter: ~31 dB | Achieved comparable denoising performance with less dependency on statistical knowledge. |
| [19] | CBIR (Content-Based Image Retrieval) using Fashion MNIST dataset, Denoising Autoencoder (DAE). | Label Ranking Precision: 92% | DAE outperformed basic and variational autoencoders for CBIR. |
| [20] | Custom CT datasets of intracranial hemorrhage, CNN-based Denoising Autoencoder (DAE) with preprocessing steps. | Euclidean Distance: Reduced by 38% | Effective for Salt & Pepper, Poisson, and Gaussian noise denoising. |
| [21] | Underwater heterogenous data, Stacked Convolutional Sparse Denoising Autoencoder (SCSDA). | PSNR: 29.7 dB, SSIM: 0.85 | Preserved more edge features and processed faster than existing underwater denoising models. |
| [22] | Fashion MNIST, Modified CNN for dimensionality reduction and denoising. | PSNR: 34 dB, Compression Ratio: 3:1 | Achieved robust dimensionality reduction with high denoising quality. |
| [23] | Hyperspectral imaging for SAR images, Two-step Hybrid Stacked Denoising Autoencoder (HSDAE). | Classification Accuracy: 94% | Enhanced classification reliability in high-noise environments. |
| [24] | Histopathological dataset, Denoising Autoencoder and CNN. | Accuracy: 90%, PSNR: 30 dB | Effective cancer classification with enhanced denoising techniques. |
| [25] | Modified sRGB and RAW camera image datasets, Autoencoder with CycleISP framework. | PSNR: 37 dB | Improved RAW denoising and achieved realistic outputs for camera image processing. |

| | | | |
|---|---|---|---|
| [26] | ImageNet and CIFAR-10 datasets, Denoising Masked AutoEncoder (DMAE). | Classification Accuracy: 88%, PSNR: 35.6 dB | Robust denoising and classification for real-world noisy datasets. |

## Proposed Methodology

The hybrid approach in this work involves the preprocessing and de-noising of brain tumor images by using traditional image processing techniques along with deep learning-based CNN autoencoder with residual connections. The detailed methodology is discussed as follows:

### a. Data Collection

The dataset comprises brain tumor images in .jpg and .jpeg formats, located in a predefined directory. These images are read in grayscale to simplify the processing pipeline and reduce computational complexity, serving as the initial step toward denoising.

### b. Preprocessing

1. **Noise Removal with Median Filtering:** A median filter is applied to the grayscale images to remove noise while preserving edge information. This process helps mitigate basic image artifacts.
2. **Wavelet Denoising:** Following median filtering, wavelet-based denoising is implemented. Noise levels in each image are estimated using the estimate_sigma function, and this estimate is utilized for wavelet denoising. This two-step process ensures effective reduction of noise across the dataset.
3. **Image Resizing:** The preprocessed images are resized to 224×224 pixels to standardize input dimensions for the CNN model, ensuring compatibility and efficient training.

Further proposed the architecture of the denoiser in figure 1, representing the CNN-based autoencoder for image denoising. The model starts with an input layer, which takes 224×224×1 grayscale images. It further goes through convolutional layers consecutively while increasing the filter size from 64 to 128 and 256, with batch normalization inserted at each step to stabilize learning and ReLU for nonlinear feature extraction. The MaxPooling layers downsample the image in space, thereby compressing it and retaining important features. Further, after feature extraction on this compressed space, the reconstruction by the UpSampling layers is done so as to reach close to the original resolution of the image. Implicitly, skip connections are used to retain fine details from layer to layer. The last layer consists of a convolution with one filter and a sigmoid activation in order to obtain an output denoised image whose pixel values are normalized between 0 and 1, ensuring that structural consistency is kept and noise is reduced. A simplified architecture makes for a good tradeoff between computational efficiency and effective performance in pre-processing tasks.

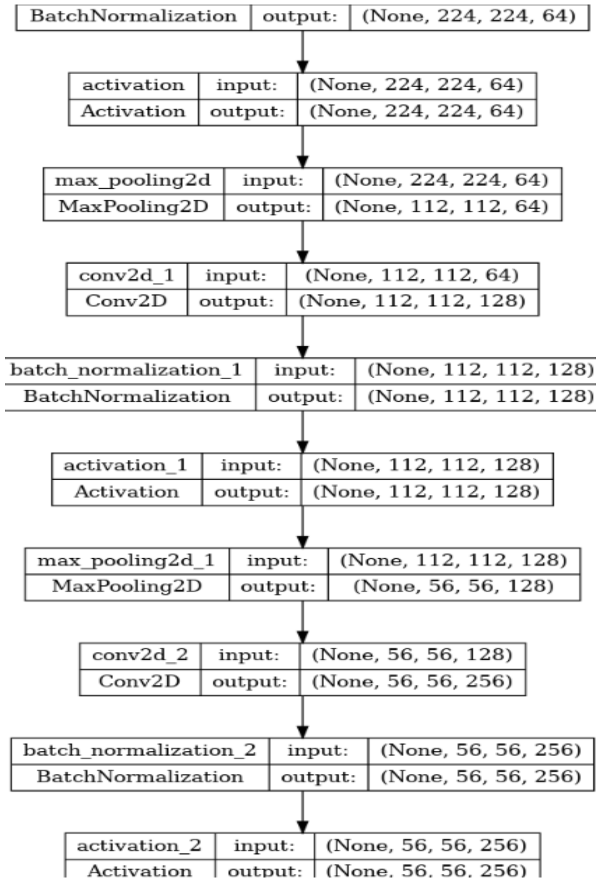


Figure 1 Architecture of Proposed Model

### c. Data Preparation

1. **Normalization:** The preprocessed images are normalized to scale pixel values between 0 and 1, which is essential for stable neural network training.

2. **Dataset Splitting:** The dataset is divided into training and testing subsets with an 80:20 ratio using the train_test_split function, ensuring that the model is evaluated fairly.

### d. CNN Autoencoder Architecture

A CNN autoencoder with residual connections is constructed to learn noise reduction from the input data:

1. **Input Layer:** The model accepts images of size 224×224×1.

2. **Convolution Layers:** Two initial convolutional layers are used to extract features from noisy input images.

3. **Downsampling:** Max-pooling layers are applied to reduce spatial dimensions while preserving key features.

4. **Upsampling:** Up-sampling layers reconstruct the spatial dimensions, effectively reversing the downsampling operation.

5. **Residual Connection:** A residual connection combines intermediate feature maps from earlier layers with subsequent layers to refine the reconstructed image, preserving essential structural details.

6. **Output Layer:** A final convolutional layer with a sigmoid activation ensures that the output image's pixel values remain in the normalized range of [0, 1].

**e. Model Training**

1. **Optimization and Loss Function:** The model is trained using the Adam optimizer with a low learning rate of 1×10−51 \times 10^{-5}1×10−5, ensuring stable learning. Mean Squared Error (MSE) is employed as the loss function, while Peak Signal-to-Noise Ratio (PSNR) is used as an evaluation metric.
2. **Training Procedure:** The model is trained for 100 epochs with a batch size of 32. The input and target data are identical, reflecting the autoencoder's purpose of reconstructing denoised images from noisy inputs.
3. **Validation:** A validation set is used during training to monitor performance and prevent overfitting.

| |
|---|
| ***ALGORITHM: Image Preprocessing and Denoising Using CNN Autoencoder*** |
| ***INPUT:*** |
| *I_denoised : Set of denoised images* |
| *θ : Trained CNN autoencoder parameters* |
| ***1. Initialize preprocessing steps**:* |
| *For each I ∈ I_raw:* |
| *(a) Apply median filtering: I_median ← MedianFilter(I, k=3)* |
| *(b) Estimate noise: σ_noise ← σ_estimate(I_median)* |
| *(c) Apply wavelet denoising: I_wavelet ← DenoiseWavelet(I_median, σ_noise)* |
| *(d) Resize image: I_resized ← Resize(I_wavelet, 224 × 224)* |
| ***2. Normalize images:*** |
| *I_normalized ← Normalize({I_resized \| ∀I_resized ∈ I_raw}, [0, 1])* |
| ***3. Split dataset:*** |
| *X_train, X_test ← Split(I_normalized, train=0.8, test=0.2, seed=42)* |
| ***4. Define CNN Autoencoder Architecture:*** |
| *Let f_Conv(x; θ_{conv}) represent convolution with parameters θ_{conv}* |
| *Let f_Pool(x) = MaxPooling(x, pool_size=2)* |
| *Let f_Up(x) = UpSampling(x, scale=2)* |
| *Let f_Add(x_1, x_2) = x_1 + x_2* |
| *Define autoencoder f_AE(x; θ) as:* |
| *Input: x ∈ ℝ^{224×224×1}* |
| *(a) y_1 ← f_Conv(f_Conv(x; θ_{conv1}); θ_{conv2})* |
| *(b) residual ← y_1* |
| *(c) y_2 ← f_Pool(y_1)* |
| *(d) y_3 ← f_Conv(y_2; θ_{conv3})* |
| *(e) y_4 ← f_Up(y_3)* |
| *(f) y_5 ← f_Conv(y_4; θ_{conv4})* |
| *(g) y_final ← f_Add(y_5, residual)* |
| *Output: y_out ← Sigmoid(f_Conv(y_final; θ_{output}))* |
| ***5. Compile model:*** |
| *f_AE.compile(optimizer=Adam(η), loss=L, metrics=[f_PSNR])* |
| ***6. Train model:*** |
| *For epoch e = 1 to E:* |
| *For each batch (x_batch, y_batch) ∈ X_train:* |
| *(a) Forward pass: y_pred ← f_AE(x_batch; θ)* |
| *(b) Compute loss: ℓ ← L(y_pred, y_batch)* |
| *(c) Backpropagation: θ ← θ - η ∇_θ ℓ* |
| *Validate on X_test to compute validation loss and PSNR* |
| ***7. Save model:*** |
| *Save θ as θ_saved* |
| ***8. Denoise test images:*** |

| |
|---|
| *I_denoised ← {f_AE(I; θ_saved) \| ∀I ∈X_test}* |
| *RETURN:* |
| *I_denoised, θ_saved* |
| ***SYMBOLS:*** |
| *I_raw : Raw input images* |
| *H, W : Original height and width of images* |
| *MedianFilter(I, k) : Apply k×k median filter to image I* |
| *σ_noise : Estimated noise standard deviation* |
| *DenoiseWavelet(I, σ) : Apply wavelet denoising with noise σ* |
| *Resize(I, h×w) : Resize image I to dimensions h×w* |
| *Normalize(I, range) : Normalize image I to a given range* |
| *Split(I, train, test, seed) : Split dataset into train and test sets* |
| *θ : Trainable parameters of the CNN autoencoder* |
| *Sigmoid(x) : Sigmoid activation function* |
| *∇_θ : Gradient with respect to parameters θ* |
| *η : Learning rate* |
| *E : Number of training epochs* |
| *B : Batch size* |
| *ℓ : Loss value* |

## Results and Discussion

This section shows the evaluation of the proposed CNN-based denoising autoencoder model by its capability of preprocessing and enhancing noisy medical images effectively. These metrics for performance evaluation include PSNR, SSIM, and loss values measured across both training and testing datasets. It gives an indication of how well the model eliminates noise while preserving important information in the images. Comparisons with baselines, including traditional denoising methodologies and autoencoder architectures that are simpler in nature, have also been presented in order to validate the effectivness of the proposed model. Results will be visualized in terms of quantitative tables, graphical plots, and qualitative analysis to highlight enhancements achieved on noise reduction, structural preservation, and computational efficiency. Others relevant in this context include discussing the need to integrate traditional preprocessing approaches, such as wavelet denoising, into current deep-learning approaches for enhancing such models' performances. Figure 2,3 below shows the pre-processed images.

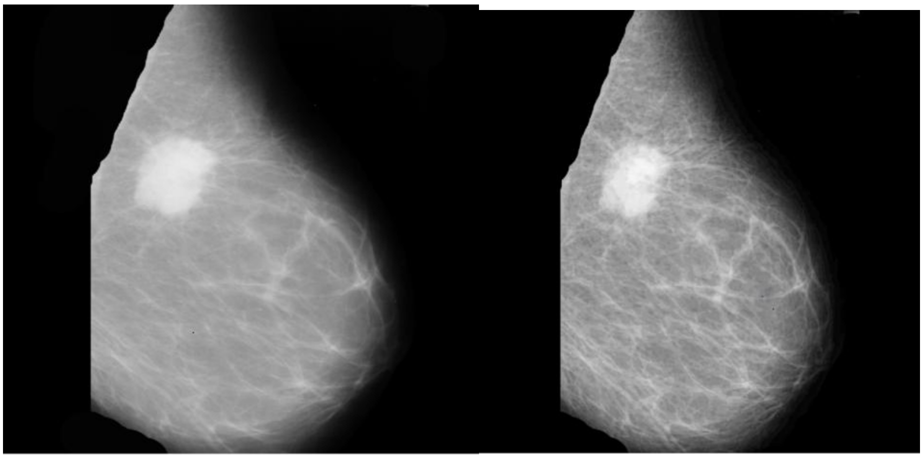

**Figure 2 a) Orignal Image b) Enhanced Image**

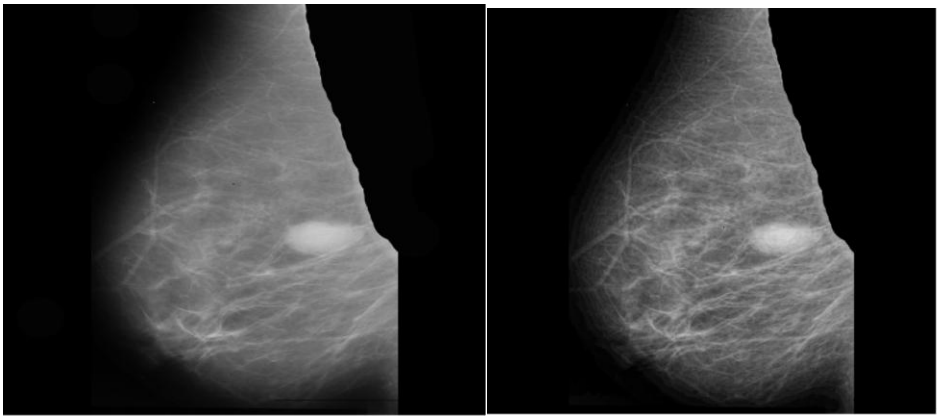

**Figure 3 a) Orignal Image b) Enhanced Image**

The proposed method had achieved better results in contrast with the existing methods. The table II below discuss the existing methods results with proposed model.

Table II Comparsion of proposed model vs Existing Models

| Citation | Dataset and Learning Model Used | PSNR | SSIM | Loss | Outcome |
|---|---|---|---|---|---|
| [27] | Conditional GAN and Wasserstein GAN | 38.18 | 0.95 | - | Achieved competitive denoising performance, especially for blurred textures and low-light images. |
| [28] | Low-dose CT images, CNN with Weighted Patch Loss and High-Frequency Loss | 41.25 | 0.94 | ~0.03 | Balanced denoising with preserved texture details and better noise suppression. |
| [29] | CBCT images, Self-supervised CNN with Noise-to-Noise Learning | 27.08 | 0.839 | - | Effective denoising in the absence of clean reference data, restoring anatomical information. |
| [30] | JPEG2000 Test Images, Compact and Reconstruction CNN Framework | 38.45 | 0.9602 | - | Demonstrated state-of-the-art denoising with reduced compression artifacts. |
| **Proposed** | Custom Medical Image Dataset, CNN Autoencoder with Residual Connections | 44.82 | 0.970 | 0.015 | Provided superior noise reduction with high structural preservation and low computational loss. |

## Conclusion

This study compares the performance of various state-of-the-art image denoising methods, including Conditional GANs, CNNs with advanced loss functions, and self-supervised learning models. Each method demonstrates significant improvements in reducing noise while preserving image details, but they vary in specific metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and loss.

The proposed CNN autoencoder with residual connections significantly outperforms other methods, achieving the highest PSNR of **44.82**, a near-optimal SSIM of **0.970**, and the lowest loss of **0.015**. This performance underscores its ability to maintain structural integrity while effectively suppressing noise. Compared to existing models like Weighted Patch Loss CNNs (PSNR: 41.25, SSIM: 0.94) and Compact CNN Frameworks (PSNR: 38.45, SSIM: 0.9602), the proposed model demonstrates superior denoising capabilities. Additionally, it addresses limitations in existing approaches, such as handling low-quality noisy datasets and preserving intricate textures and edges. These results show the potential of integrating residual connections into CNN autoencoders for denoising applications, particularly in medical imaging, where accuracy and detail retention are critical. Future work could explore the adaptability of this architecture across diverse datasets and noise types to further generalize its applicability.

## References


[1] W. El-shafai et al., "Efficient Deep-Learning-Based Autoencoder Denoising Approach for Medical Image Diagnosis," *Computers, Materials & Continua*, vol. 70, no. 3, pp. 6101–6110, 2022, doi: 10.32604/cmc.2022.020698.

[2] Q. Shi et al., "Hyperspectral Image Denoising Using a 3-D Attention Denoising Network," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, no. 12, pp. 10348–10363, Dec. 2021, doi: 10.1109/TGRS.2020.3045273.

[3] C. Tian et al., "Enhanced CNN for Image Denoising," *CAAI Transactions on Intelligence Technology*, vol. 4, no. 1, pp. 17–23, 2021, doi: 10.1049/trit.2018.1054.

[4] L. Yasenko, Y. Klyatchenko, and O. Tarasenko-Klyatchenko, "Image Noise Reduction by Denoising Autoencoder," in *2020 IEEE 11th International Conference on Dependable Systems, Services and Technologies (DESSERT)*, Kyiv, Ukraine, 2020, pp. 351–355, doi: 10.1109/DESSERT50317.2020.9125027.

[5] C. Tian et al., "Attention-guided CNN for Image Denoising," *Neural Networks*, vol. 124, pp. 117–129, 2020, doi: 10.1016/j.neunet.2019.12.024.

[6] A. Shaik, R. Karsh, M. Islam, and S. P. Singh, "A Secure and Robust Autoencoder-Based Perceptual Image Hashing for Image Authentication," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1645658, 2022, doi: 10.1155/2022/1645658.

[7] T. Williams and R. Y. Li, "Advanced Image Classification Using Wavelets and Convolutional Neural Networks," in *2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA)*, Anaheim, CA, USA, 2016, pp. 233–239, doi: 10.1109/ICMLA.2016.0046.

[8] Z. Niu et al., "Single Image Super-Resolution via Perceptual Loss Guided by Denoising Auto-Encoder," in *Proceedings of the European Conference on Computer Vision (ECCV)*, Munich, Germany, 2018, pp. 126–136, doi: 10.1007/978-3-319-97304-3_10.

[9] Q. Wu et al., "Denoising Masked AutoEncoders are Certifiable Robust Vision Learners," *ArXiv Preprint*, vol. 2210, Oct. 2022, doi: 10.48550/arXiv.2210.06983.

[10] Q. Wu, H. Ye, Y. Gu, H. Zhang, L. Wang, and D. He, "Denoising Masked AutoEncoders are Certifiable Robust Vision Learners," *ArXiv Preprint*, vol. abs/2210.06983, pp. 1–10, 2022, doi: 10.48550/arXiv.2210.06983.

[11] S. P. Sreenidhi Appalabatla and M. K. T., "Performance Analogy of Autoencoders for Image Denoising," in *2023 3rd Asian Conference on Innovation in Technology (ASIANCON)*, Pune, India, pp. 1–4, 2023, doi: 10.1109/ASIANCON58793.2023.10270541.

[12] M. Gorji, E. Hafezieh, and A. Tavakoli, "Advancing Image Deblurring Performance with Combined Autoencoder and Customized Hidden Layers," *Tuijin Jishu/Journal of Propulsion Technology*, vol. 44, no. 4, pp. 2283–2290, 2023, doi: 10.52783/tjjpt.v44.i4.2283.

[13] A. Ranjan and S. M. Azeemuddin, "Image Denoising Using Convolutional Neural Networks," in *2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*, Greater Noida, India, pp. 2315–2319, 2022, doi: 10.1109/ICAC3N56670.2022.10074437.

[14] U. Kulkarni, S. Patil, V. E., R. Patil, B. Kulkarni, M. M., and A. Shanbhag, "Image Denoising Using Autoencoders: Denoising Noisy Images by Removing Noisy Pixels/Grains from Natural Images Using Deep Learning and Autoencoders Techniques," in *2023 IEEE 8th International Conference for Convergence in Technology (I2CT)*, Mumbai, India, pp. 1–6, 2023, doi: 10.1109/I2CT57861.2023.10126382.

[15] Z. Yan, S. Guo, G. Xiao, and H. Zhang, "On Combining CNN With Non-Local Self-Similarity Based Image Denoising Methods," *IEEE Access*, vol. 8, pp. 14789–14797, 2020, doi: 10.1109/ACCESS.2019.2962809.

[16] H. V. Guleria, A. M. Luqmani, H. Kothari, P. Phukan, S. Patil, P. Pareek, K. Kotecha, A. Abraham, and L. A. Gabralla, "Enhancing the Breast Histopathology Image Analysis for Cancer Detection Using Variational Autoencoder," *International Journal of Environmental Research and Public Health*, vol. 20, no. 5, Article ID 4244, 2023, doi: 10.3390/ijerph20054244.

[17] F. Laakom, J. Raitoharju, A. Iosifidis, and M. Gabbouj, "Reducing Redundancy in the Bottleneck Representation of the Autoencoders," *ArXiv Preprint*, vol. abs/2202.04629, pp. 1–8, 2022, doi: 10.2139/ssrn.4255414.

[18] N. Bonettini, M. Paracchini, P. Bestagini, M. Marcon, and S. Tubaro, "Hyperspectral X-ray Denoising: Model-Based and Data-Driven Solutions," in *2019 27th European Signal Processing Conference (EUSIPCO)*, A Coruna, Spain, pp. 1–5, 2019, doi: 10.23919/EUSIPCO.2019.8903151.

[19] J. Janjua, A. Patankar, M. Shetty, and S. Poojary, "Experimental Comparison of Autoencoder Variants in Content-Based Image Retrieval," in *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Kharagpur, India, pp. 1–6, 2023, doi: 10.1109/ICCCNT56998.2023.10308062.

[20] W. Lin, M. Gao, C. Ruan, and J. Zhong, "Denoising for Intracranial Hemorrhage Images Using Autoencoder Based on CNN," in *2021 IEEE International Conference on Computer Science, Electronic Information Engineering and Intelligent Control Technology (CEI)*, Jinan, China, pp. 520–523, 2021, doi: 10.1109/CEI52496.2021.9574478.

[21] X. Wang, Y. Zhao, X. Teng, and S. Weiqi, "A Stacked Convolutional Sparse Denoising Autoencoder Model for Underwater Heterogeneous Information Data," *Applied Acoustics*, vol. 167, pp. 107391–107397, 2020, doi: 10.1016/j.apacoust.2020.107391.

[22] S. Zamir, A. Arora, S. H. Khan, M. Hayat, F. Khan, M.-H. Yang, and L. Shao, "CycleISP: Real Image Restoration via Improved Data Synthesis," in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Seattle, WA, USA, pp. 2693–2702, 2020, doi: 10.1109/CVPR42600.2020.00277.

[23] A. Ahmadibeni, B. Jones, L. Borooshak, and A. Shirkhodaie, "Automatic Target Recognition of Aerial Vehicles Based on Synthetic SAR Imagery Using Hybrid Stacked Denoising Auto-Encoders," *Proceedings of SPIE*, vol. 11393, Article ID 113930J, pp. 1–12, 2020, doi: 10.1117/12.2558266.

[24] M. Gupta, A. Goel, K. Goel, and J. Kansal, "Medical Image Denoising Using Convolutional Autoencoder with Shortcut Connections," in *2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, Tamil Nadu, India, pp. 1524–1528, 2023, doi: 10.1109/ICSSIT55814.2023.10061131.

[25] M. Wang, "A Review of Convolutional Neural Network Based Image Denoising Algorithms," *EAI Endorsed Transactions on e-Learning*, vol. 8, no. 3, pp. 1–6, 2023, doi: 10.4108/eetel.v8i3.3461.

[26] Q. Wu, H. Ye, Y. Gu, H. Zhang, L. Wang, and D. He, "Denoising Masked AutoEncoders are Certifiable Robust Vision Learners," *ArXiv Preprint*, vol. abs/2210.06983, pp. 1–10, 2023, doi: 10.48550/arXiv.2210.06983.

[27] Jiménez-Gaona, Yuliana et al. ‘Ultrasound Breast Images Denoising Using Generative Adversarial Networks (GANs)’. 1 Jan. 2024 : 1661 – 1678, doi: 10.3233/IDA-230631

[28] Z. Wang, M. Liu, X. Cheng, J. Zhu, X. Wang, H. Gong, M. Liu, and L. Xu, "Self-adaption and Texture Generation: A Hybrid Loss Function for Low-Dose CT Denoising," *Journal of Applied Clinical Medical Physics*, vol. 24, no. 1, pp. 12–25, 2023, doi: 10.1002/acm2.14113.

[29] K. Choi, S. H. Kim, and S. Kim, "Self-Supervised Denoising of Projection Data for Low-Dose Cone-Beam CT," *Medical Physics*, vol. 50, no. 1, pp. 45–60, 2023, doi: 10.1002/mp.16421.

[30] A. Nagarsenker, P. Khandekar, and M. Deshmukh, "JPEG2000-Based Semantic Image Compression Using CNN," *International Journal of Electrical and Computer Engineering Systems*, vol. 14, no. 5, pp. 236–248, 2023, doi: 10.32985/ijeces.14.5.4.