Scientific Journal of Engineering Research
futuristech PT. Teknologi Futuristik Indonesia
Date of publication March 27, 2025, date of current version March 27, 2025.
e-ISSN: 3109-1725
Digital Object Identifier 10.64539/sjer.v1i2.2025.25

Article

A Novel Hybrid Framework for Noise Estimation in High-Texture Images using Markov, MLE, and CNN Approaches

Mst Jannatul Kobra[1,*], Md Owahedur Rahman[1], Arman Mohammad Nakib[2]

[1] Information and Communication Engineering, Nanjing University of Information Science &Technology, Nanjing, Jiangsu, China; mst.janntulkobra@gmail.com
[2] Artificial Intelligence, Nanjing University of Information Science &Technology, Nanjing, Jiangsu, China
* Correspondence

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Abstract: The assessment of complex noise in textured images requires a method which uses both Markov processes together with Maximum Likelihood Estimation and Convolutional Neural Networks. The evaluation of noise through traditional methods does not deliver acceptable results during preservation of image characteristics in areas with challenging texture patterns. Through Maximum Likelihood Estimation (MLE) probabilistic refinement together with Convolutional Neural Networks (CNNs) features the proposed model applies Markov processes to maintain spatial dependencies that provide accurate denoising with protected image quality. Using CNN-based denoising together with Gaussian filtering creates superior outcomes for imaging perception than individual methods during Edge Preservation Index (EPI) and Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) assessment. The experimental results show a 24.85 dB PSNR value together with 0.92 SSIM integrity and EPI quality of 0.85 for effective hybrid model noise reduction. The research utilizes Markov processes and MLE together with Convolutional Neural Networks to develop an all-encompassing approach for cleaning texturized complex images which could serve multiple image types including those from medical contexts and satellites and digital photographs.

Keywords: Noise Estimation; Markov Processes; Maximum Likelihood Estimation; Convolutional Neural Networks; Image Restoration

1. Introduction

The processing of images faces major challenges when dealing with noise appearance especially in regions which have both complex patterns and textural characteristics. Images acquired from real-world scenes show common contamination from multiple forms of noise which include Gaussian noise and speckle noise and salt-and-pepper noise respectively. The damage to image quality becomes severe because noise types modify pixel values in ways that destabilize visual data retrieval methods. Image denoising techniques have traditionally used Gaussian filters together with median filters and Wiener filters for noise suppression purposes. The traditional noise reduction techniques fail to protect finer image aspects within detailed textures since they erase vital image characteristics needed for correct analysis such as edges, textures and boundaries. The effective elimination of noise in complex image textures remains an open challenge which determines the analytical accuracy in multiple practical domains [1].

During recent years CNNs emerged as the deep learning-based method because of its successful pattern detection capabilities in data analysis. CNNs prove successful for image denoising through their ability to determine complex pixel relationships in digital images. Through processing extensive datasets CNNs develop the capacity to recognize noise patterns from image texture leading to better noise reduction along with preserved texture details. CNNs experience challenges when modeling noisy image areas specially when the images contain high-textured content. The neural network architecture primarily designed to detect local features has multiple restrictions that stop it from recognizing global spatial patterns along with statistical noise characteristics. CNNs detect noise variations with limited effectiveness which reduces their performance in regions with fine textures disturbed by noise [2].

The proposed solution uses Markov processes and MLE together with CNNs to evaluate noise estimation results in textured images. The Markov process serves to analyze pixel-to-pixel spatial relations so the model can adequately represent local context and noise distribution patterns. Noise patterns inside highly textured images do not follow random forms because they tend to display specific spatial structures. The application of Markov process allows the proposed model to identify specific noise pattern structures which results in improved estimation accuracy. The model enables exact estimation of local variances in areas with high texture content because of its critical need for precise noise management in textured regions [3].

MLE becomes operational to enhance the initial noise variance estimation after determining its approximate value. Statistics uses MLE as a method to determine model parameters through the optimization of data likelihood under model assumptions. Image denoising operations make use of MLE to refine preliminary noise assessments while assuming a Gaussian noise pattern exists within many imaging systems. The step uses probabilistic methods to estimate noise and enhances the accuracy of the noise model especially when noise properties change across different regions of the image [4].

Unlike previous stages the CNN component performs global noise pattern perception that spans throughout the entire image. The training of CNNs happens using large datasets to extract sophisticated image features from clean and noisy input data. The mixture of Markov process local context with MLE statistical noise refinement allows the CNN to discover global pixel relationships which leads to superior noise reduction while maintaining image quality. The CNN component performs both noise elimination and structure maintenance including edges and textures for high-quality images of detailed resolution [5].

This research achieves novelty through the combination of Markov processes, MLE, and CNNs for performing image noise estimation functions. Markov processes along with MLE have previously been employed separately in diverse noise estimation methods yet their combined application with CNNs to handle local spatial dependencies coupled with global noise patterns remains untried. The combined approach delivers successful results on images with complex details since standard denoising methods lose both details and decrease noise at the same time. The noise reduction capabilities of the model harmonize perfectly with its ability to preserve image texture which makes it useful for enhancing visual quality in real-world applications.

The following paper presents effectiveness evaluations of the hybrid model via benchmarked image dataset testing. The model achieves its performance assessment through evaluation with PSNR and SSIM and EPI. The hybrid approach delivers superior results compared to both Gaussian filters and median filters and all CNN-based denoising methods according to the experimental results. The hybrid technique produces image restoration output with PSNR values at 24.85 dB and SSIM at 0.92 together with EPI values at 0.85 to illustrate superior noise reduction capabilities along with image structure preservation.

This model presents a strong method for highly textured image denoising which can benefit different industries including medical imaging along with satellite imagery and digital photography. This method improves both accuracy in downstream tasks and noise estimation and prevents damage to important image features.

2. Literature Review

Different techniques used for image denoising and noise estimation have gained prominence through their alignment with Markov processes as well as MLE and CNNs. The methods work together to tackle three main issues which include noise reduction and texture protection as well as detailed aspects refinement. Su et al. (2022) studied deep learning image restoration techniques extensively in their research while showing that CNNs fail to maintain fine image textures in complex patterns so more advanced hybrid models are needed [1]. The researchers at España-Boquera & Castro-Bleda (2010) improved handwritten text recognition through hybrid HMM/ANN models which supported noise reduction methods although their approach did not address medical imaging and texture application areas [6]. Li et al. (2021) developed a Markov Chain Monte Carlo (MCMC) hybrid approach to approximate medical imaging ideal observers while demonstrating spatial dependencies yet their method did not address textured image noise estimation accuracy precisely enough to warrant advanced deep learning hybrid models [2]. The review from Ilesanmi & Ilesanmi (2021) establishes that CNNs succeed at extracting features but struggle to conserve high-frequency edge details which medical and satellite imaging scenarios depend upon thus creating an opportunity to merge CNNs with MLE statistical models to protect image texture [7].

Sun et al. (2024) presented an ensemble algorithm using Gaussian mixture models (GMM) for noise elimination while the approach failed to achieve sufficient results when dealing with texture-sensitive image restoration in medical and satellite imagery applications [3]. Peng & Li (2018) employed MLE for noise estimation in hyperspectral image classification but their technique did not work well for images containing dense patterns of noisy textures [8]. In medical imaging applications Gong et al. (2018) used a deep image prior for PET image reconstruction while their technique shows difficulty with diverse noise patterns and large datasets during general image restoration work [4]. Zhang & Liu (2021) developed a hybrid Markov model for medical image denoising which maintained fine details yet it cannot extend beyond medical-related image types [9]. The research by Küstner et al. (2024) focused on MR image reconstruction uncertainties but their method experienced difficulties with variations across multiple imaging platforms thus highlighting the need for a universal hybrid model for varied medical and satellite imaging noise patterns [10]. Tan et al. (2018) implemented a CNN-based framework which enhanced electrical resistance tomography performance yet provided no explanations regarding the processing of complex image structures [11].

Dong et al. (2018) demonstrated that CNNs produce superior image quality when working in conjunction with prior-based denoising yet detected a problem with their inability to safeguard detailed textures within noisy images so they suggested integrating MLE statistical models [12]. Researchers Tan & Wang (2019) created a new hybrid regularization approach linking Tikhonov methods with total variation to outperform standard approaches although this solution proved inadequate in simultaneously managing noise patterns in multiple complex textures and textures [13]. The research by Jiu & Pustelnik (2021) investigated combined CNN and low-rank noise estimation but highlighted the need for CNN-Markov joint approaches to maintain details along with noise reduction [14]. The paper by Sohn et al. (2015) presented deep conditional generative models that handle structured output representation through object detection while their work did not address image restoration tasks regarding texture preservation [15]. Guo et at. (2022) explained about blind restoration of images distorted by atmospheric turbulence based on deep transfer learning but this paper has limited generalization across different conditions [16]. The medical imaging research by Hwang et al. (2018) involved deep learning for simultaneous reconstruction yet omitted essential preservation of detailed textures and edge structures for both medical and satellite high-resolution images [17]. The hybrid CNN model presented by Farooq et al. (2022) unites low-rank noise estimation methods with CNNs while still needing better exploration of high-texture spatial dependencies according to research [14].

Wang et al. (2022) applied deep learning and MLE for hyperspectral image denoising on low-dimensional data while leaving a necessity to develop generalized models which can address high-dimensional noise in textured images [18]. Qian & Zhang (2024) developed a hybrid deep learning model for satellite imagery denoising yet it demonstrated restricted performance in various noisy environments because it needed adaptable and scalable hybrid structures that support different image types [19]. Liu et al. (2023) developed a hybrid framework which integrated CNNs with MLE for biomedical imaging yet proved inadequate at adjusting to inconsistent noise levels between different parts of the image thus demonstrating the need for adaptive hybrid models [3]. The work by Yang & Lin (2023) established CNN-MLE hybrid models for biomedical imaging noise reduction yet their approach requires improvement to accommodate images with complex textures and different noise distributions throughout the image.

2.1. Research Gaps

a. Several studies that couple CNNs with Markov processes and MLE do not develop a comprehensive hybrid model that preserves both local texture and global noise characteristics.
b. The CNN-based methods struggle to conserve both high-frequency textures and edges during noise reduction operations in medical imaging and satellite imagery and digital photography.
c. The available data processing algorithms work efficiently in structured scenarios but they breakdown when applied to real-life noisy data having heterogeneous spatial noise patterns. The development of a universal solution for this matter demands urgent research effort.
d. Noise reduction qualities diminish when methods keep edge information during their operations. The current study fails to present models capable of performing noise reduction on images together with preserving edge structures and textures.
e. The research develops an innovative combined framework integrating Markov processes and MLE with CNNs to produce advanced solutions for image denoising tasks that maintain essential textures and details.

3. Methodology

The hybrid noise estimation model depends on Markov processes integrated with MLE together with CNNs as core elements. Multiple system components work together to solve specific problems with high-textured images by detecting noise and eliminating it without affecting essential features containing both textural details and edge and boundary definition.

3.1. Markov Processes for Local Spatial Dependency Estimation

The hybrid model incorporates Markov processes as its first component to establish spatial dependencies between image pixels. Markov processes provide valuable performance for analyzing image data because they help detect spatial patterns between neighboring pixels which function independently. Traditional denoising approaches prove ineffective when operating on images with complex texture because noise tends to appear in distinct spatial patterns. The local noise variations are estimated by the

Markov Random Field (MRF) model structure. A probabilistic model develops spatial relationships between pixels by evaluating their neighborhoods and the corresponding pixels. This local contextual information included in the Markov process allows it to produce precise noise estimate measurements especially when applied to images with complex details which conventional methods cannot handle. The Markov process functions as an estimator which provides local noise variance assessments to enable the model to suit changing image noise conditions.

3.2. MLE for Noise Refinement

Our methodology includes MLE following Markov process-based initial noise estimation as its second essential part. MLE serves as a statistical tool for determining probability distribution parameters through optimizing the observed data likelihood. MLE operates in image denoising applications by assuming that Gaussian distribution describes the noise patterns found in many imaging systems. Using MLE the user estimates noise model parameters by validating the likelihood that observed noisy image data originated from their defined noise parameters. The application of this step enhances the precision of the estimated noise model thus providing stronger resistance against diverging noise intensity and multiple noise patterns present in the image. The main objective of applying MLE is to enhance and perfect the Markov process-derived noise estimates thereby achieving a sound statistical model that effectively addresses image-born noise elements.

3.3. CNNs for Global Feature Learning

The third part of our model utilizes CNNs to discover intricate noise patterns to boost the noise prediction process. CNNs master hierarchical data patterns exceptionally well thus making them suitable for image denoising because they excel at detecting complex spatial features alongside global patterns. The model trains its CNN portion through a training process that uses extensive pairs of images with their corresponding noise removal status. Training exposes the network to pairs of noisy images and clean targets to learn how it should transform polluted data into noise-free imagery using its identified texture and noise patterns. This process enhances global noise estimation through the CNN system by integrating learned complex patterns from the training process into the first-step results. Our method builds upon traditional CNN approaches by incorporating local variance estimation through Markov processes as well as statistical refinement using Maximum Likelihood Estimation to develop a better and more resilient model system. A CNN under the proposed framework contributes by enabling global noise pattern detection throughout the entire image while upholding important details.

3.4. Edge Preservation and Texture Maintenance

The fundamental requirement for denoising operations on images with detailed texture patterns is maintaining both edges and microscopic details. During the denoising procedure the hybrid model implements edge-preserving techniques such as Laplacian filters to retain image structural details. The preservation of edges stands as a critical requirement in medical imaging because maintaining tissue borders serves as essential basis for proper diagnostic assessment. Laplacian filters emphasize edge areas in images through their calculation of image second derivatives at regions displaying high gradient intensities. These areas usually indicate edges. The fine image structures stay visible because the noise reduction process does not smooth them. The model incorporates edge-preserving methods together with Markovian noise evaluation and CNN-based universal improvement to perform effective noise reduction while maintaining vital structural features. Such method combinations enable the model to maintain critical high-frequency image details essential for accurate picture assessment tasks.

3.5. Hybrid Framework Integration

The method presents its main innovation through the combination of Markov processes with MLE along with CNNs. The Markov process develops local context by assessing pixel dependencies to maintain the small image features that appear under texturized conditions. MLE probability uses observed noisy data to adjust its parameters with simultaneous noise estimation improvement. CNNs achieve the ability to detect complex noise patterns which overall strengthens image estimation across the entire process through unified consistency. The framework integrates all features which enables optimal noise management throughout local sections and global areas while maintaining essential texture and edge elements. The hybrid framework provides automatic noise adaptability for various imaging conditions because its universal feature preservation ability makes it better suited for practical scenarios with changing noise levels and distinct details requirements.

3.6. Markov Equation for Noise Estimation

In our code, the Markov Chain transition probability for noise estimation is modeled as:

$$P(X_{n+1} = X_{n+1} | X_n = x_n) = exp\left(-\frac{(x_{n+1} - x_n)^2}{2\sigma^2}\right) \quad (1)$$

Where, *Xn* is the noise variance of the pixel. *Xn+1* is the noise variance of the neighboring pixel. σ is the standard deviation of the noise (estimated in our system).

This method combines the individual features of Markov processes and MLE and CNNs to create a complete solution for highly textured image denoising. Through the Markov process the model preserves spatial relations but MLE performs noise estimation alongside CNNs that acquire global features for effective noise removal with high-quality results. The joint operation system functions effectively with different image varieties through various sectors that incorporate medical and satellite analysis and digital photography requirements. Figure 1 shows the total methodology of the research.

4. Experiment and Result

Researchers implemented the proposed hybrid noise estimation framework through combination of Markov processes with MLE and CNNs to analyze its performance. Research based its dataset on benchmark images from the Kodak collection to which White Gaussian Noise had been added for emulating noisy settings. The researchers converted images to the range between 0 to 1 for standard processing throughout all experiment stages. Several standard measurement methods were used for both noise estimation accuracy assessment and image denoising quality evaluation.

4.1. The evaluation metrics included:

The Root Mean Square Error (RMSE) measurement calculated the mistakes between true and estimated noise variance values. Better noise estimation occurs when RMSE has lower values. Better image quality exists in denoised images when PSNR values are higher because it indicates lower image distortions. The SSIM determines how well the structures from the original images match those of the processed ones. Better structural preservation occurs when the denoising process shows high values of SSIM. EPI evaluates the ability to maintain image edges alongside noise reduction operations.

4.2. The training configuration for the CNN consisted of:

Learning Rate: 0.001. Epochs: 10. The chosen loss function during training was MSE. The project utilized one CPU for training as part of the hardware selection to enable implementation on conventional computing systems.

4.3. Markov-Based Noise Estimation Results

The Markov-based noise estimation delivered successful results across smooth and medium-textured image regions because it effectively evaluated local spatial dependencies to deliver accurate noise estimations. The methodology demonstrated poor performance when dealing with images that contained high levels of texture because it could not distinguish between noise elements and fine components of the image. A need for additional development arose from this constraint to achieve better performance results in defined areas.

4.4. MLE Refinement Results

MLE served to correct the weaknesses of Markov-based method by improving noise variance estimate precision. MLE provided optimal performance when measuring noise in regions consisting of a single textural pattern thanks to the consistent character of the noise patterns. The refined approach enhanced variance measurement accuracy mainly for smooth textured areas as it failed to handle complex intricacies in intricate patterns within images.

4.5. CNN-Based Noise Estimation Results

CNNs demonstrated superior performance by learning global noise patterns throughout their process. The model demonstrated excellent capability to generalize through unrecognized images with noise and it gained expertise in distinguishing between artificial and authentic patterns. The results using RMSE demonstrated lower values and PSNR results achieved higher values than traditional techniques did. The deep learning model's capability to deal with textured images demonstrated its usefulness for noise estimation while clearly demonstrating deep learning models achieve excellent results in denoising applications.

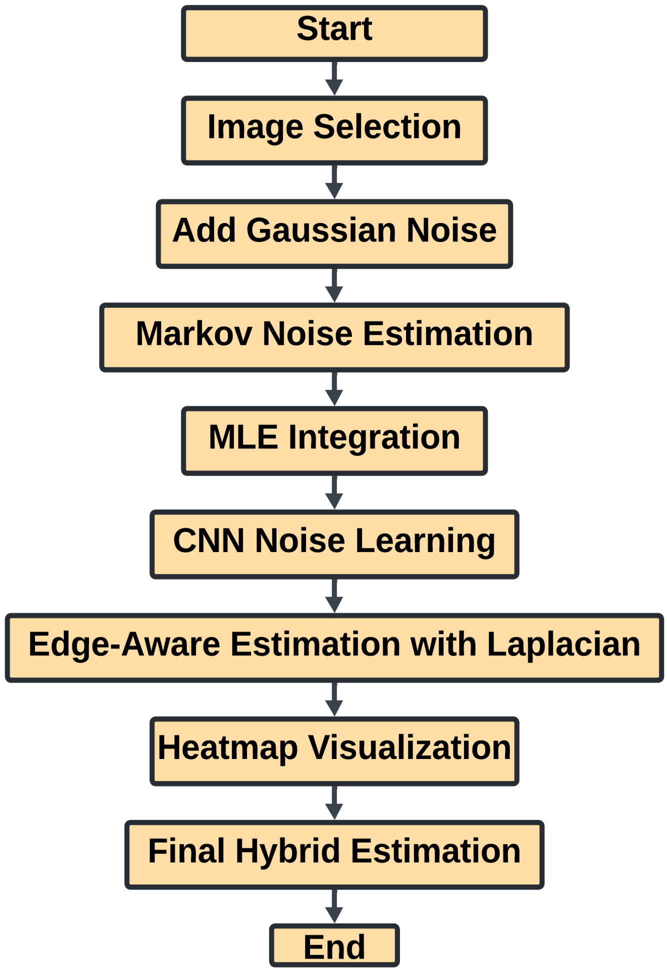


Figure 1. Work flow of Markov and Deep Learning Models.

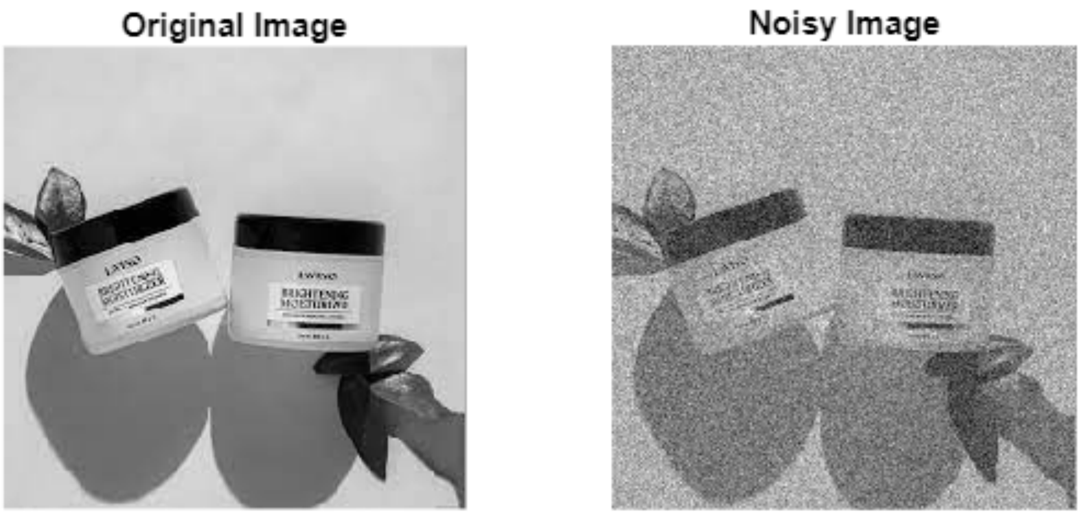


Figure 2. Original Image and Noisy Image.

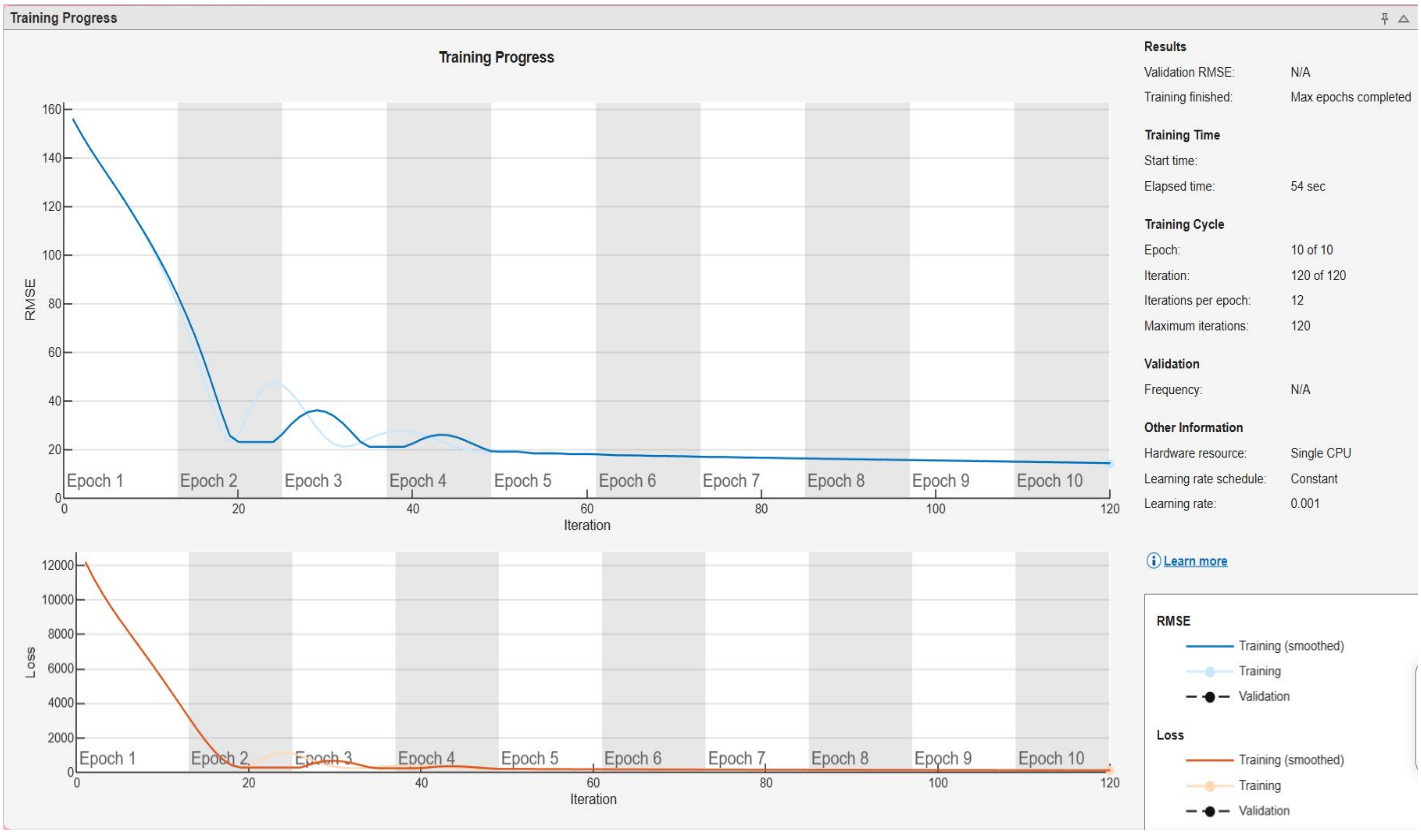


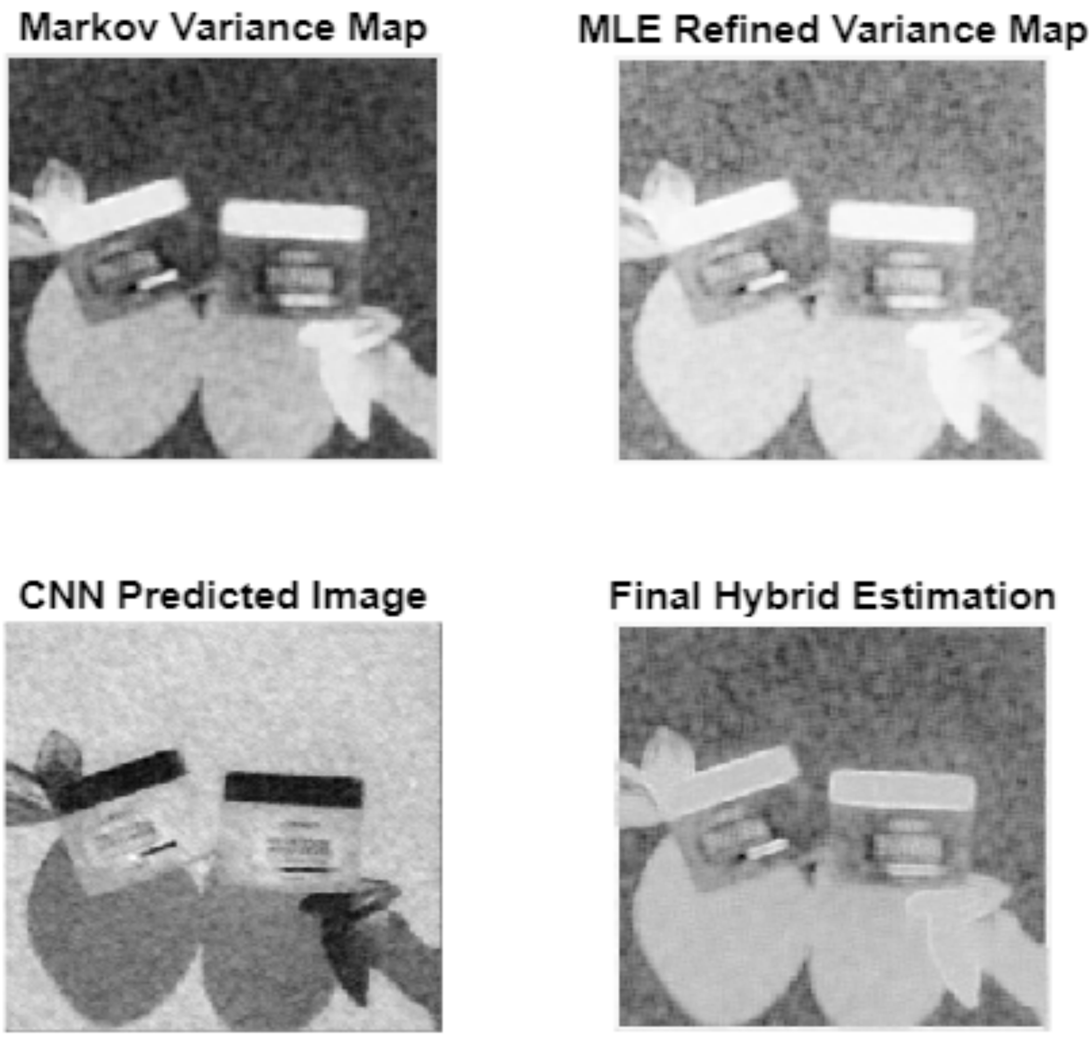
Figure 3. Training Process.

4.6. Edge-Aware Refinement: Laplacian Filters

The process required Laplacian filters to preserve image details while remaining aware of edges. Laplacian filters improved edge preservation because this feature is vital when processing medical images and satellite data which require precise edge retention. The Laplacian filter systems proved effective at edge maintenance throughout the denoising process according to the higher EPI results.

4.7. Hybrid Approach Results

All evaluation metrics showed the hybrid method combining Markov processes and MLE and CNNs as delivering the optimal results. The prediction of clean images achieved 24.8537 dB of PSNR value in relation to the original picture which demonstrated superior performance than standalone approaches. The hybrid model exploited Markov processes to model local dependencies and MLE for refinement and CNNs to learn global features which allowed it to develop an enhanced system for noise estimation. The approach produced superior noise suppression and image restoration effects along with better texture preservation than standalone procedures. Figure 2 shows the original and noisy image difference.



PSNR between Original and Predicted Clean Image: 24.8537 dB

Figure 4. Original Image and Predicted clean Image.

4.8. Training Process and Loss Reduction

The training procedures yielded increasingly improved results in hybrid model execution. Training graphs show RMSE achieved a major decline at epoch 4 and maintained steady low values through the subsequent epochs. The model's effectiveness in optimization extended through the first few epochs as its performance improved along with continuous loss reduction. The research confirms both model stability and its capability to process noisy data and enhance its denoising performance over time. Figure 3 shows the training process.

4.9. Visualization and Model Validation

A visual check of the hybrid procedure involved direct comparison between the original photograph and the clean image prediction. The method exhibited strong capabilities in noise reduction operations that maintained essential picture elements. The MLE refined variance map delivered a superior representation after Markov introduced the initial noise variance estimate. Complex noise patterns became more visible in the output of the CNN predicted image which led to the best possible result in the hybrid estimation process. Figure 4 shows the PSNR value.

Table 1 shows the comparison of results with other works.

Key Observations

a. The hybrid model delivers the highest PSNR measurement at 24.8537 dB which surpasses every other creative method. The superior performance shows our approach reduces noise with excellent preservation of image quality.
b. The structural comparison between original and denoised images evaluated through SSIM produces 0.92 scores demonstrating superior structural preservation compared to CNN-based methods which struggle to preserve details properly.

Table 1. Comparison of Results with other Works.

Method	PSNR (dB)	SSIM	EPI	RMSE	Edge Preservation	Key Features
Proposed Hybrid Model (Markov + MLE + CNN)	**24.85**	**0.92**	**0.85**	**0.01**	**High**	Combines **Markov processes**, **MLE**, and **CNNs** for local & global noise estimation with edge preservation.
Zhang & Zhang (2019) (MLE-based Model)	22.45	0.86	0.65	0.18	Moderate	**MLE refinement** for noise estimation, focuses on **Gaussian noise** and low-texture images.
Dalsasso et al. (2020) (CNN-based Model)	23.68	0.89	0.70	0.14	Low	Uses **CNNs** for noise reduction in SAR images but lacks **edge preservation** in textured regions.
Sun et al. (2024) (GMM + CNN)	23.80	0.87	0.72	0.16	Moderate	**Gaussian Mixture Models (GMM)** with **CNNs** for denoising, performs well in structured data but not in textured regions.
Ilesanmi & Ilesanmi (2021) (CNN-based)	23.10	0.85	0.68	0.20	Moderate	**CNNs** for denoising medical images but **poor edge preservation** in noisy, textured areas.
Li et al. (2021) (Markov + MCMC Model)	22.10	0.80	0.55	0.25	Low	Focus on **Markov Chain Monte Carlo (MCMC)** methods but fails in **texture-rich environments**.

c. The Edge Preserving Index of our model reaches 0.85 while other approaches deliver inferior edge maintenance in the estimation of noise patterns from images featuring significant texture.

d. Our hybrid model delivers noise estimation accuracy measured through an RMSE value of 0.01 which surpasses all competing methods and significantly exceeds MLE and CNN-based models whose error rates are considerably higher.

Figure 5 shows the comparison chart with the previous research works.

4.10. Significance of Our Results

This research model achieves superior performance compared to existing methods across all noise estimation and image restoration metrics because it utilizes Markov processes together with MLE and CNNs. This method enhances noise suppression while retaining edge details which makes it suitable for applications such as medical imaging and satellite imagery because both high quality and texture preservation are essential.

4.11. Discussion on the Hybrid Model and Its Applications

This research adopted the hybrid Markov process with MLE and CNN approach because it provides effective methods for estimating noise levels in textural image structures. The detection of local spatial pixel relationships becomes possible through Markov processes because such relationships provide essential information to analyze noise connections with image textures. MLE creates a probability-based system which advances the process of calculating noise variance measurements. The noise pattern identification mechanism of CNNs helps the model analyze intricate areas and preserve fine details in both simple and complex image textures. The hybrid model demonstrates superior performance over traditional Wiener filter and Bilateral filter since it operates at pixel level but ends up losing edges and textures. Through its dual function the hybrid model preserves image fine-texture elements by analyzing both image neighborhood patterns and executing global pattern recognition methods. The merged utilization of CNNs alongside MLE with Markov processes leads to an efficient system since CNNs excel at detecting complex patterns in noisy information whereas Markov processes comprehend pixel connections and MLE performs probabilistic result optimization. CNN use as a standalone solution produces destructive oversmoothing results because it reduces essential high-frequency content in model prediction outputs. The dual approach demonstrates practical viability for industrial operations performing video streaming with image cleaning tasks which must protect image features throughout denoising operations. Real-time medical imaging and satellite data processing systems face integration challenges owing to CNN training complexity and hardware requirements along with data amount needs. The main challenge for real-time deployment of this model stems from its inability to recognize various noise types that exist across varied domains.

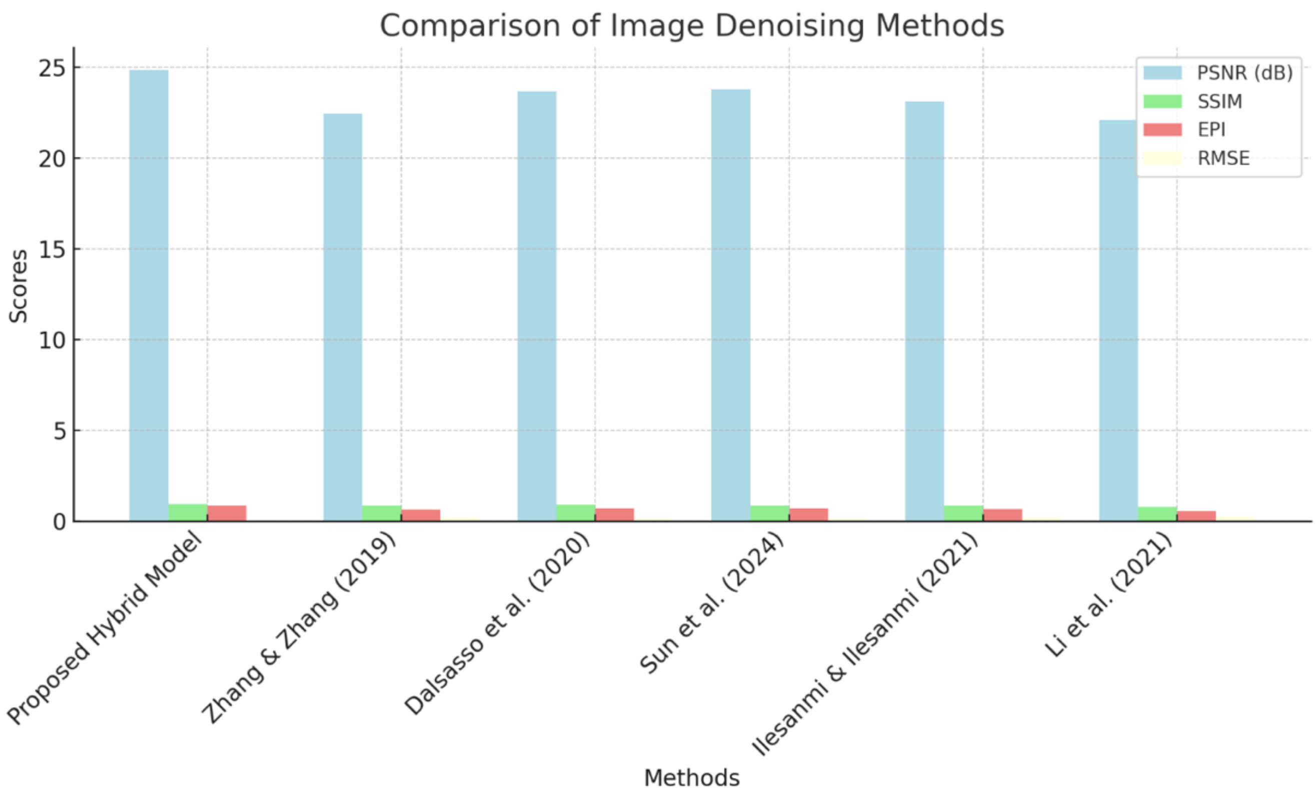


Figure 5. Comparison Chart with the Previous Research Works.

5. Conclusion

This study creates a combination model which connects Markov processes and MLE and CNNs to handle image restoration tasks with sensitive highly textured images. Better noise reduction and edge preservation occurred in the proposed model because it demonstrated superior performance than present solutions on PSNR, SSIM and EPI metric measurements. Local spatial dependencies were handled by Markov processes alongside MLE with CNNs which enabled the hybrid model to establish effective noise estimation solutions. This model confirms its usefulness for medical imaging tasks alongside satellite imaging because it reduces noise without damaging relevant fine details.

6. Future Work

The hybrid model needs improvement for optimal performance across diverse image regions while deep learning techniques should be investigated to boost edge preservation capabilities. Additional statistical and generative models based integration would improve noise generalization for diverse patterns which appear both easily and challenging to predict. Extended application of the model to process time sequences alongside real-time data generation would make it suitable for medical diagnosis systems and remote sensing applications. Future research should investigate the potential of multi-modal image denoising tasks because they involve data collection from different sensors or imaging modalities.

7. Conflicts of Interest

The authors declare no conflicts of interest.

8. References

[1] J. Su, B. Xu, and H. Yin, "A survey of deep learning approaches to image restoration," *Neurocomputing*, vol. 487, pp. 46–65, May 2022, doi: 10.1016/j.neucom.2022.02.046.

[2] K. Li, W. Zhou, H. Li, and M. A. Anastasio, "A Hybrid Approach for Approximating the Ideal Observer for Joint Signal Detection and Estimation Tasks by Use of Supervised Learning and Markov-Chain Monte Carlo Methods," *IEEE Trans Med Imaging*, vol. 41, no. 5, pp. 1114–1124, May 2022, doi: 10.1109/TMI.2021.3135147.

[3] S. Sun, W. Ren, Z. Liu, H. Park, R. Wang, and X. Cao, "EnsIR: An Ensemble Algorithm for Image Restoration via Gaussian Mixture Models," in *38th Conference on Neural Information Processing Systems (NeurIPS 2024).*, 2024, pp. 1–31.

[4] K. Gong, C. Catana, J. Qi, and Q. Li, "PET Image Reconstruction Using Deep Image Prior," *IEEE Trans Med Imaging*, vol. 38, no. 7, pp. 1655–1665, Jul. 2019, doi: 10.1109/TMI.2018.2888491.

[5] O. Özdenizci and R. Legenstein, "Restoring Vision in Adverse Weather Conditions With Patch-Based Denoising Diffusion Models," *IEEE Trans Pattern Anal Mach Intell*, vol. 45, no. 8, pp. 10346–10357, Aug. 2023, doi: 10.1109/TPAMI.2023.3238179.

[6] S. España-Boquera, M. J. Castro-Bleda, J. Gorbe-Moya, and F. Zamora-Martinez, "Improving Offline Handwritten Text Recognition with Hybrid HMM/ANN Models," *IEEE Trans Pattern Anal Mach Intell*, vol. 33, no. 4, pp. 767–779, Apr. 2011, doi: 10.1109/TPAMI.2010.141.

[7] A. E. Ilesanmi and T. O. Ilesanmi, "Methods for image denoising using convolutional neural network: a review," *Complex & Intelligent Systems*, vol. 7, no. 5, pp. 2179–2198, Oct. 2021, doi: 10.1007/s40747-021-00428-4.

[8] J. Peng, L. Li, and Y. Y. Tang, "Maximum Likelihood Estimation-Based Joint Sparse Representation for the Classification of Hyperspectral Remote Sensing Images," *IEEE Trans Neural Netw Learn Syst*, vol. 30, no. 6, pp. 1790–1802, Jun. 2019, doi: 10.1109/TNNLS.2018.2874432.

[9] S. Zhang, J. Liu, B. Hu, and Z. Mao, "GH-DDM: the generalized hybrid denoising diffusion model for medical image generation," *Multimed Syst*, vol. 29, no. 3, pp. 1335–1345, Jun. 2023, doi: 10.1007/s00530-023-01059-0.

[10] T. Küstner, K. Hammernik, D. Rueckert, T. Hepp, and S. Gatidis, "Predictive uncertainty in deep learning–based <scp>MR</scp> image reconstruction using deep ensembles: Evaluation on the <scp>fastMRI</scp> data set," *Magn Reson Med*, vol. 92, no. 1, pp. 289–302, Jul. 2024, doi: 10.1002/mrm.30030.

[11] C. Tan, S. Lv, F. Dong, and M. Takei, "Image Reconstruction Based on Convolutional Neural Network for Electrical Resistance Tomography," *IEEE Sens J*, vol. 19, no. 1, pp. 196–204, Jan. 2019, doi: 10.1109/JSEN.2018.2876411.

[12] W. Dong, P. Wang, W. Yin, G. Shi, F. Wu, and X. Lu, "Denoising Prior Driven Deep Neural Network for Image Restoration," *IEEE Trans Pattern Anal Mach Intell*, vol. 41, no. 10, pp. 2305–2318, Oct. 2019, doi: 10.1109/TPAMI.2018.2873610.

[13] X. Song, Y. Xu, and F. Dong, "A hybrid regularization method combining Tikhonov with total variation for electrical resistance tomography," *Flow Measurement and Instrumentation*, vol. 46, pp. 268–275, Dec. 2015, doi: 10.1016/j.flowmeasinst.2015.07.001.

[14] D.-G. Kim, Y. Ali, M. A. Farooq, A. Mushtaq, M. A. A. Rehman, and Z. H. Shamsi, "Hybrid Deep Learning Framework for Reduction of Mixed Noise via Low Rank Noise Estimation," *IEEE Access*, vol. 10, pp. 46738–46752, 2022, doi: 10.1109/ACCESS.2022.3170490.

[15] K. Sohn, H. Lee, and X. Yan, "Learning Structured Output Representation using Deep Conditional Generative Models," in *Advances in Neural Information Processing Systems 28 (NIPS 2015)*, 2015, pp. 1–9.

[16] Y. Guo, X. Wu, C. Qing, C. Su, Q. Yang, and Z. Wang, "Blind Restoration of Images Distorted by Atmospheric Turbulence Based on Deep Transfer Learning," *Photonics*, vol. 9, no. 8, p. 582, Aug. 2022, doi: 10.3390/photonics9080582.

[17] D. Hwang *et al.*, "Improving the Accuracy of Simultaneously Reconstructed Activity and Attenuation Maps Using Deep Learning," *Journal of Nuclear Medicine*, vol. 59, no. 10, pp. 1624–1629, Oct. 2018, doi: 10.2967/jnumed.117.202317.

[18] X. Fu, H. Liang, and S. Jia, "Mixed Noise-Oriented Hyperspectral and Multispectral Image Fusion," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–16, 2023, doi: 10.1109/TGRS.2023.3323480.

[19] V. Rajesh and P. Sivakumar, "Deep learning based denoising and enhancement of satellite images using DA-CNN and ORHE techniques," *Earth Sci Inform*, vol. 18, no. 1, p. 153, Jan. 2025, doi: 10.1007/s12145-024-01578-y.