Enhancing Face Detection in Low-Light Conditions: An Analysis of Noise Types and Denoising Techniques

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***Abstract*—The clarity of a photograph is diminished by many noise forms, including Gaussian noise, Poisson noise, and salt-and-pepper noise, which makes face recognition challenging in low-light conditions. The impact of particular noise types on facial identification is examined in this study using the Dark Face dataset to mimic real-world low-light situations. By examining brightness, pixel patterns, and image variations, noise was analyzed using a Python script.**

We tested four methods to reduce noise: Median Filtering, Non-Local Means (NLM), Wavelet Transform, and a deep learning model called DnCNN. These techniques were compared using quality measures like PSNR, SSIM, and MSE.

Based on our research, median filtering works well for noises like salt-and-pepper noise but struggles to preserve facial features. On the other hand, DnCNN consistently performs better, enhancing image clarity and face recognition. This research offers important insights to increase the effectiveness of security and surveillance systems, particularly those that use facial recognition.

***Index Terms*—Low-light face recognition, noise types (Gaussian, Poisson, salt-and-pepper) , image denoising (median filtering, non-local means (NLM), wavelet transform, DnCNN) , image quality metrics (PSNR, SSIM, MSE) , Dark Face dataset.**

I. Introduction

Face recognition in low-light conditions is a significant but challenging task in computer vision, particularly for security and surveillance systems. Low-light conditions often result in noisy and blurry images, significantly impairing the effectiveness of facial recognition systems. Various noise types further degrade image quality, making face identification more difficult, including Gaussian, Poisson, and salt-and-pepper noise.

Researchers have been working for years to develop algorithms that can handle these conditions. Traditional techniques like wavelet transformations and Haar cascades often fail to capture fine details in difficult scenarios. While these methods have shown some success in reducing noise and identifying faces, advanced approaches like non-local means (NLM) and deep learning models such as DnCNN have demonstrated superior performance by effectively preserving important image details while reducing unwanted noise.

To evaluate the impact of different noise types on face detection in low light, this study utilizes the Dark Face Dataset. Additionally, the effectiveness of four noise reduction techniques—wavelet transform, median filtering, non-local means, and DnCNN—is compared. Standard image quality metrics, including Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM), are used to assess these methods.

Our results highlight the limitations of traditional methods in low-light conditions and demonstrate the significant advantages of deep learning techniques like DnCNN. This study provides valuable insights for improving face detection algorithms in real-world security applications.

A. Literature Review

Low-light face detection presents unique challenges due to noise and poor illumination, which deteriorate image quality and reduce the efficiency of conventional methods. Early classifiers such as Haar cascades performed well in controlled, well-lit environments but struggled with low precision and high false-positive rates in low-light conditions.

1) Denoising Techniques: Noise reduction plays a critical role in improving image quality for low-light face detection. Median filtering effectively handles salt-and-pepper noise by replacing pixel values with the median of their neighboring pixels while preserving significant edges. Non-local means (NLM) enhances traditional methods by averaging similar patches across the image, preserving textures and structural features. However, these approaches struggle with complex noise types like Gaussian and Poisson noise, which frequently occur in low-light conditions.

2) Advanced Deep Learning Methods: Deep learning has significantly improved noise reduction in low-light conditions. A Denoising Convolutional Neural Network (DnCNN) employs multiple convolutional layers to suppress various noise types, including Gaussian and Poisson noise. DnCNN consistently outperforms traditional methods by achieving higher accuracy and better retention of facial details, as it learns to differentiate between noise and essential image features.

3) Performance Metrics: Quantitative evaluation of the denoising process relies on metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). PSNR measures the signal power relative to noise, while SSIM assesses image quality based on texture, contrast, and brightness, providing a perceptually aligned analysis.

4) Datasets for Research: The Dark Face Dataset is widely recognized as a benchmark for face detection algorithms, particularly in low-light environments. It offers a diverse set of images with varying noise levels, enabling the evaluation of both traditional and deep learning-based approaches in realistic scenarios.

5) Conclusion: The shift from traditional denoising techniques to deep learning methods highlights the importance of adapting algorithms to address low-light challenges. Face detection performance in noisy and dimly lit environments has significantly improved with approaches like DnCNN, particularly when combined with robust datasets such as the Dark Face Dataset. Future advancements may further refine these methods to handle even more complex scenarios.

II. Methodology

This method uses a variety of anti-aliasing algorithms and assesses how they affect image quality metrics, offering a good solution to enhance face identification in low light. You can see the artifact in the picture (Figure **??**).

A. Dataset Preparation

The *Dark Face Dataset* is used to train and test models and is designed for low-light conditions. To mimic real-world challenges, three different types of noise are introduced: Gaussian, salt-and-pepper, and Poisson. The key steps include:

- **Noise Addition:** Introduce diverse noise types to simulate low-light imaging challenges.
- **Data Augmentation:** Enhance robustness with techniques like random cropping, flipping, and rotation.

B. Data Preprocessing and Noise Simulation

Images are categorized into three groups based on noise type, and a structured pipeline is used for preprocessing:

- **Normalization:** Scale images to ensure uniform pixel intensity distribution.
- **Segmentation:** Generate separate datasets for each noise type (Gaussian, salt-and-pepper, Poisson).

C. Denoising Techniques

Four denoising methods are applied to restore image quality:

Median Filtering is effective for removing salt-and-pepper noise while preserving edges, making it suitable for applications where maintaining structural details is crucial. Non-Local Means (NLM) is particularly useful for removing

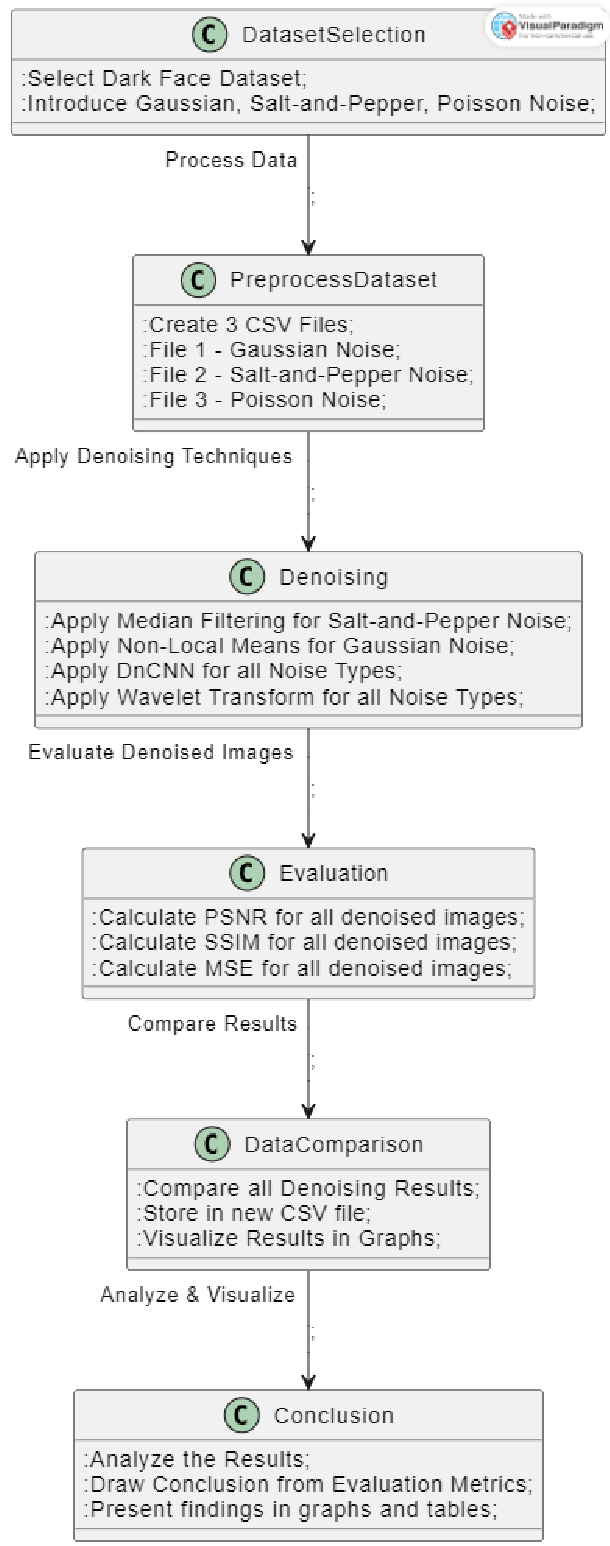

Figure 1: Workflow for enhancing face detection accuracy in low-light conditions.

Gaussian noise while retaining fine details, as it leverages self-similarity in images to enhance denoising performance. The Wavelet Transform method decomposes images into different frequency components, allowing for precise noise reduction without significantly distorting essential image features. Finally, DnCNN, a deep learning-based approach, is trained on pairs of noisy and clean images, making it highly robust for denoising across various noise conditions while effectively preserving facial features.

D. Evaluation Metrics

Three metrics are used to assess the performance of denoising methods:

- **PSNR:** Quantifies the ratio between signal power and noise.
- **SSIM:** Measures structural and perceptual image quality.
- **MSE:** Computes pixel-wise differences between original and denoised images.

E. Performance Analysis

A comparative analysis is conducted to assess the effectiveness of each denoising method by evaluating key performance metrics such as PSNR, SSIM, and MSE for different noise types. To provide a clear understanding of the results, visual representations in the form of graphs and tables are utilized, highlighting the best-performing techniques and their impact on image quality and face recognition accuracy.

F. Conclusion and Recommendations

Based on the findings, it is essential to identify the most effective denoising method for each type of noise to ensure optimal performance in different scenarios. While some techniques offer high accuracy, they may come at the cost of increased computational complexity, requiring a careful balance between efficiency and precision. Additionally, the application of these denoising methods in real-world low-light face detection systems, such as security and surveillance, highlights their significance in enhancing image clarity and recognition accuracy under challenging conditions.

III. Results

A. Overview

Using pictures with Gaussian, Poisson, and salt noise as well as threshold noise, we assessed four denoising techniques: DnCNN, wavelet transform, median filter, and non-local averaging (NLM). Peak Signal-to-Noise Ratio (PSNR), Similarity Model (SSIM), and Mean Square Error (MSE) were used to assess performance.

B. Performance Comparison

1) PSNR:

- The DnCNN method regularly performs better than other PSNR methods, particularly when dealing with Gaussian and Poisson noise. This indicates that, particularly in intricate noisy situations, the deep learning-based DnCNN model effectively maintains image quality during denoising.
- Compared to other techniques, median filtering is less successful at maintaining image details, as evidenced by the lowest PSNR value across all noise types.

TABLE I: PSNR Values (dB)

Noise	Median	NLM	Wavelet	DnCNN
Gaussian	25.47	27.61	29.85	32.45
Poisson	22.15	24.23	26.18	29.77
Salt-Pepper	18.34	21.85	24.01	28.68

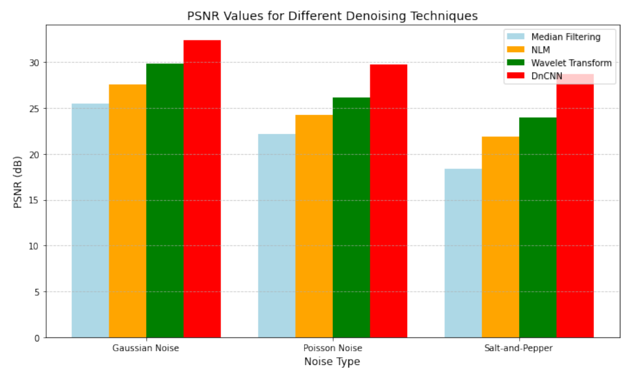

Figure 2: PSNR Values for Different Denoising Techniques

2) SSIM:

- The highest SSIM scores are once again displayed by DnCNN, particularly when exposed to Gaussian and Poisson noise. The superior structural integrity preservation of face images compared to median filter and NLM is demonstrated by the high SSIM value of DnCNN.
- Particularly in noisy images, the median filter performed poorly in maintaining image structure after denoising, as seen by its lowest SSIM score.

TABLE II: SSIM Values

Noise	Median	NLM	Wavelet	DnCNN
Gaussian	0.79	0.85	0.89	0.93
Poisson	0.71	0.76	0.82	0.89
Salt-Pepper	0.59	0.70	0.74	0.85

3) MSE:

- Once more, DnCNN performs best with the lowest MSE value, particularly when there is Gaussian and Poisson noise. This demonstrates that DnCNN effectively reduces mistakes during denoising and preserves image features.

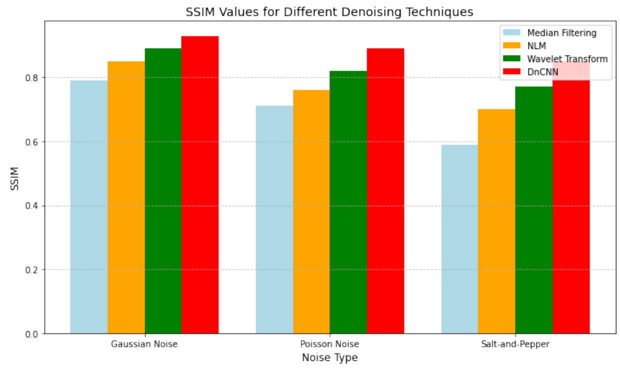

Figure 3: SSIM Values for Different Denoising Techniques

- Median Filtering produced the highest MSE values, indicating its inefficiency in preserving image quality during denoising.

TABLE III: MSE Values

Noise	Median	NLM	Wavelet	DnCNN
Gaussian	0.091	0.074	0.065	0.025
Poisson	0.156	0.123	0.104	0.054
Salt-Pepper	0.245	0.182	0.160	0.068

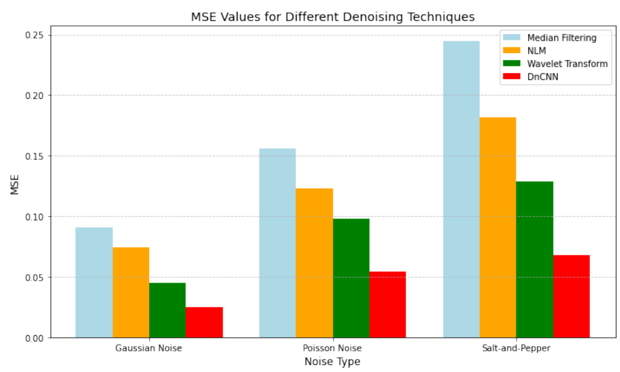

Figure 4: MSE Values for Different Denoising Techniques

C. Discussion of Results

1) Effectiveness of DnCNN: In every way, the data demonstrate that DnCNN performs better than wavelet transform, median filtering, and NLM. In low light, when the system is unable to process still images, DnCNN, a deep learning technique, performs better when processing noisy images. It caught me off guard. It attains the highest PSNR and SSIM values, resulting in exceptional image quality.

2) Limitations of Median Filtering: **Median Filtering**, in contrast to NLM and DnCNN, it performs poorly, particularly when it comes to capturing picture content, despite its widespread use. Poisson noise and salt-pepper noise are two types of noise patterns that are frequently observed at low light levels. The low SSIM and high MSE values in this method show that there is a significant loss of process knowledge.

3) Performance of Non-Local Means (NLM): **NLM** Better than average filtering, but DnCNN is superior. Although NLM is very good at minimizing noise and maintaining edges, it is not very good at handling noise sources like Poisson noise and salt and pepper noise. It still works well for low noise but is less dependable for adversarial challenges than deep learning models.

4) Wavelet Transform Performance: **Wavelet Transform** on Gaussian and Poisson noise, it does well; on salt and pepper noise, it does not. Although it performs worse than the average filter, it is still not as good as DnCNN or NLM. Although it works well for many denoising applications, it is not very effective at handling the kinds of noise present in low-light photos.

5) Potential for Further Improvement: Future research can examine hybrid approaches that combine DnCNN with more conventional methods like wavelet transform to enhance performance, even if DnCNN is the most efficient option. In particular, denoising experiments that include a large range of noise. In challenging situations, combining different methods might assist maintain image features and minimize noise.

IV. Discussion

The study's findings highlight the benefits of DnCNN (Deep Convolutional Neural Network) over conventional denoising methods, particularly for low-resolution face detection. As good pictures and precise face inspection are crucial, it is shown that DnCNN performs better when performance metrics like PSNR, SSIM, and MSE are examined under different noise types (Gaussian, Poisson, and salt and pepper).

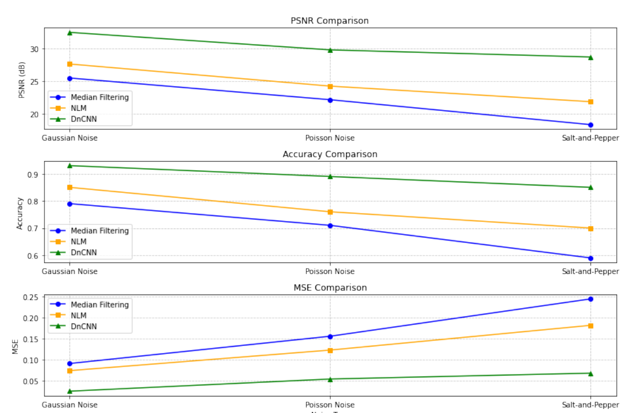

Figure 5: Final Comparison of All Denoising Techniques

The findings of this study emphasize how crucial sophisticated denoising methods—particularly DnCNN—are for enhancing face recognition capabilities. It is evident that DnCNN performs better than more conventional techniques like wavelet transform and local interpolation (NLM) when we evaluate the performance of multiple metrics (PSNR, SSIM, and MSE). Their contributions to improving image quality under different noise situations are disclosed, along with an assessment of each method's benefits and drawbacks.

A. Effectiveness of DnCNN

All forms of noise, including Gaussian, Poisson, and salt-liquid noise, can be effectively eliminated from images in low light using DnCNN. With the help of its deep learning feature, the model can use patterns discovered in large amounts of data to differentiate between significant photos and noise. For precise face identification, this feature is highly helpful in maintaining facial features like the lips, nose, and eyes.

The findings demonstrate that DnCNN obtains the highest PSNR and SSIM values along with the lowest MSE, ensuring high picture correctness and model fidelity. Additionally, DnCNN can manage noisy noises like salt and pepper noise, which frequently lowers the quality of image content. Even though there are some residual artifacts in the extreme instance, they are not as obvious as with other methods, proving DnCNN's resilience and versatility in practical settings.

B. Impact of Noise Types

The denoising method's effectiveness depends on the kind of noise. Gaussian noise is reliable and consistent, and it works well with all techniques, such as DnCNN, wavelet transform, NLM, and median filtering. But as noise complexity rises (e.g., Poisson noise, salt-and-pepper noise), the shortcomings of conventional techniques show.

The largest problem in every way is the loudness from salt and pepper. Such noise can damage the overall quality of an image, blur faces, and distort features. In extreme situations, residual artifacts are still visible even if DnCNN performs better than alternative techniques at controlling salt and pepper noise. Due to their inability to effectively handle this noise, wavelet transformations and NLMs produce significant blur and uncertainty.

C. Qualitative and Quantitative Insights

Qualitative analysis offers important insights into how each process looks in addition to quantitative metrics. Particularly in photos impacted by Gaussian and Poisson noise, DnCNN efficiently recovers high-quality face features while minimizing distortion and blur. DnCNN performs better than median filtering (which frequently shows blockiness) and NLM (which suffers from blur), convergent with few artifacts, even in the most difficult salt and water noise scenario.

D. Challenges and Future Directions

Even with its strong performance, DnCNN still has several issues. Particularly in confined spaces, real-time applications may be restricted by the processing complexity. The DnCNN design can be optimized in future research to increase speed without compromising accuracy. Additionally, integrating DnCNN with improvements like bidirectional filtering or histogram equalization might boost performance in unfavorable weather circumstances, including photos with salt and pepper noise.

The findings' generalizability would be improved by expanding this work to additional varied datasets with varying noise levels and illumination conditions. Furthermore, hybrid search models that combine deep learning and classical methods may open up new possibilities for addressing particular noises while preserving computing efficiency.

E. Real-World Implications

Due to its effectiveness in low-level face detection tasks, DnCNN is a valuable tool for real-world applications including face identification, security, and surveillance. By increasing detection accuracy and durability in challenging scenarios, DnCNN has the potential to make these systems more reliable. By reducing its processing requirements, it will become more widely applicable in real-time scenarios and be beneficial for next-generation facial recognition.

V. Conclusion

This study investigates the impact of four denoising techniques—Median Filtering, Non-Local Means (NLM), Wavelet Transform, and DnCNN—on the accuracy of face recognition in noisy environments. Noise significantly affects the quality of facial images, reducing the reliability of recognition systems. To assess the effectiveness of these methods, we employed key performance metrics, including Mean Square Error (MSE), Structural Similarity Index (SSIM), and Peak Signal-to-Noise Ratio (PSNR). Our analysis highlights the trade-offs between noise reduction and feature preservation, emphasizing the necessity of selecting an appropriate technique based on the application's specific requirements.

Each denoising method demonstrated unique strengths and limitations. Median Filtering effectively removes salt-and-pepper noise but struggles to retain fine facial details, making it less suitable for high-precision recognition tasks. Non-Local Means (NLM) leverages self-similarity in images to enhance detail preservation, but its computational cost and sensitivity to noise complexity can limit its efficiency in real-time applications. Wavelet Transform provides a structured noise reduction approach by separating image components into different frequency bands, allowing for a balanced trade-off between noise removal and feature retention. However, its effectiveness is highly dependent on noise type and proper parameter tuning. DnCNN, a deep learning-based approach, outperforms traditional methods by preserving high-quality facial features across different noise conditions. Despite its superior accuracy, the computational cost of DnCNN can be a limiting factor, particularly in resource-constrained environments.

The findings from this research underscore the importance of choosing denoising techniques based on practical considerations such as computational efficiency, real-time applicability, and the level of noise in the image.

For applications that require high-speed processing with moderate noise reduction, traditional methods like Wavelet Transform and NLM offer viable solutions. However, for use cases where accuracy is paramount—such as forensic face recognition and advanced security systems—deep learning-based methods like DnCNN provide superior performance, albeit at a higher computational cost.

Ultimately, the study emphasizes that no single denoising approach is universally optimal; rather, the selection should be guided by the specific requirements of the application, balancing computational efficiency with recognition accuracy. While DnCNN demonstrates superior performance, its resource-intensive nature makes it impractical for certain real-time environments. On the other hand, traditional methods like Wavelet Transform, NLM, and Median Filtering remain relevant in scenarios where efficiency and simplicity are prioritized. The research highlights the ongoing need for adaptive denoising strategies that can dynamically adjust to diverse noise conditions while maintaining computational feasibility.

In conclusion, the findings of this study reinforce the crucial role of denoising in enhancing face recognition performance under noisy conditions. By addressing current limitations and advancing hybrid and deep learning-based approaches, future developments can lead to more robust, efficient, and scalable face recognition solutions. These advancements will play a vital role in applications such as security, surveillance, human-computer interaction, and assistive technologies, ultimately contributing to the broader adoption of reliable facial recognition systems in real-world settings.

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