Comparative Analysis of Preprocessing Techniques for Enhanced Facial Recognition under Challenging Conditions

[1]Awodeyi, Afolabi I., [2]Ibok, Omolegho A., [3]Idama, Omokaro, [4]Ekwemuka, Jones U., [5]Ebem, Deborah U., [6]Mamah, Rotenna O, [7]Ugwu, Obinna C.

[1,2,3,4] Department of Computer Engineering, Delta State University of Science and Technology, Ozoro Nigeria

[5,6,7]Department of Computer Engineering, Veritas University Abuja, Nigeria.

DOI: https://doi.org/10.51244/IJRSI.2025.12020004

Received: 08 January 2025; Revised: 16 January 2025; Accepted: 20 January 2025; Published: 26 February 2025

ABSTRACT

Facial recognition systems often face challenges in scenarios with low-light conditions and occlusions, where critical facial features are obscured or poorly illuminated. This paper investigates the effectiveness of various preprocessing techniques, such as histogram equalization, gamma correction, and noise reduction, in enhancing facial recognition performance under such challenging conditions. Visual comparisons of images before and after preprocessing are included to demonstrate tangible improvements. Additionally, the computational efficiency and resource trade-offs of combined preprocessing techniques are analyzed, providing insights into their practical applicability. By integrating these techniques with facial recognition models, significant improvements in accuracy and feature extraction capabilities can be achieved. The methodology outlines the applied techniques and the experimental setup used for comparative analysis. Results indicate that certain preprocessing strategies, when used in combination, yield superior performance in handling difficult conditions. This study provides insights into optimizing preprocessing pipelines for robust facial recognition.

Index Terms- Preprocessing Techniques, Low-Light Conditions, Occluded Facial Recognition, Image Enhancement, Performance Analysis

INTRODUCTION

Facial recognition technology has become an essential component in various applications, including security, surveillance, and user authentication. However, the effectiveness of these systems can be hindered by suboptimal conditions such as poor lighting and partial occlusions, which compromise the visibility of key facial features. These challenges necessitate the use of preprocessing techniques that enhance image quality, enabling models to extract more reliable features.

Preprocessing techniques, such as histogram equalization, gamma correction, and noise reduction, play a crucial role in enhancing image clarity and contrast. These methods help mitigate the effects of shadows, glare, and obstructions, thus improving the overall accuracy of facial recognition systems. This paper aims to analyze and compare the impact of these preprocessing techniques on facial recognition performance under low-light and occluded conditions, offering recommendations for optimal preprocessing strategies.

LITERATURE REVIEW

Histogram Equalization

Histogram equalization is a widely used preprocessing technique that improves image contrast by redistributing the intensity values across an image [1]. This method is particularly effective in low-light scenarios, where images often suffer from poor contrast. Shan et al. [2] demonstrated that applying histogram equalization to facial images resulted in more distinguishable features and improved recognition rates in low-light environments.

However, the technique can sometimes lead to over-enhancement, creating noise in areas where contrast changes are abrupt [3]. Bourlai et al. [4] noted that combining histogram equalization with other preprocessing steps could mitigate these drawbacks and result in more balanced image enhancement.

Gamma Correction

Gamma correction adjusts the brightness of an image through a nonlinear transformation, enhancing darker areas without significantly affecting the brighter regions [5]. This technique is useful for normalizing illumination in facial images, especially those captured in environments with uneven lighting. Naik [3] showed that applying gamma correction improved feature visibility and recognition accuracy, particularly in shadow-heavy images.

Research by Alagarsamy et al. [6] indicated that gamma correction, when used alongside histogram equalization, provided a robust preprocessing pipeline that maintained facial feature integrity while enhancing visibility. This combined approach was particularly beneficial for images with variable lighting conditions [3], [7].

Noise Reduction

Noise reduction techniques, such as Gaussian filtering and median filtering, are employed to remove unwanted noise that can obscure facial features and reduce recognition accuracy [8]. By smoothing the image, noise reduction ensures that the recognition model focuses on essential features rather than noise artifacts. Gupta et al. [7] highlighted the importance of noise reduction in improving recognition rates, especially in images captured under low-light conditions.

Studies by Ryumina et al. [8] showed that noise reduction, when applied before other enhancement techniques like histogram equalization, resulted in cleaner, more defined images, allowing for better feature extraction. Noise reduction can be particularly useful when dealing with occlusions, as it enhances the clarity of visible regions and reduces the impact of obstructions [9]-[10].

Combined Preprocessing Techniques

Combining multiple preprocessing techniques can yield better results than applying them individually. Romdhani et al. [10] demonstrated that preprocessing pipelines integrating histogram equalization, gamma correction, and noise reduction significantly improved recognition rates in challenging conditions. Similarly, studies by Georgescu and Ionescu [9] showed that a hybrid approach enhanced model performance, making it more resilient to occlusions and poor lighting [11]-[12].

METHODOLOGY

Preprocessing Techniques Overview

The preprocessing techniques evaluated in this study include:

i) **Histogram Equalization**: Enhances image contrast by redistributing pixel intensity values.
ii) **Gamma Correction**: Adjusts image brightness using a nonlinear transformation to normalize illumination using gamma value of 0.5.
iii) **Noise Reduction**: Applies Gaussian filtering to smooth the image and remove noise artifacts with a kernel size of 5×5.

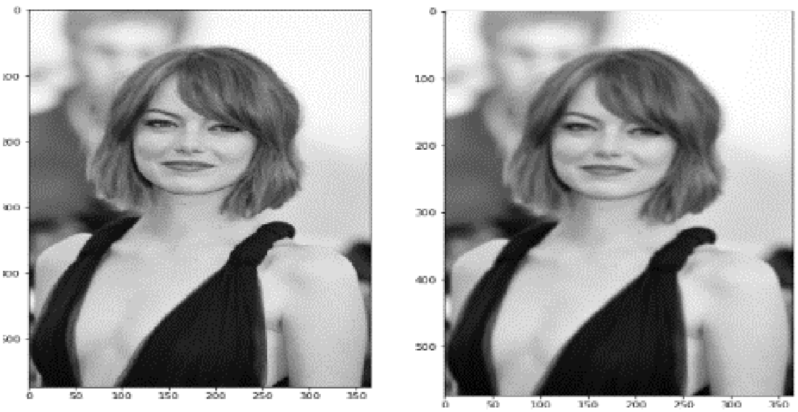
These techniques were applied individually and in combination to assess their impact on facial recognition performance.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue II February 2025

Integration with Recognition Models

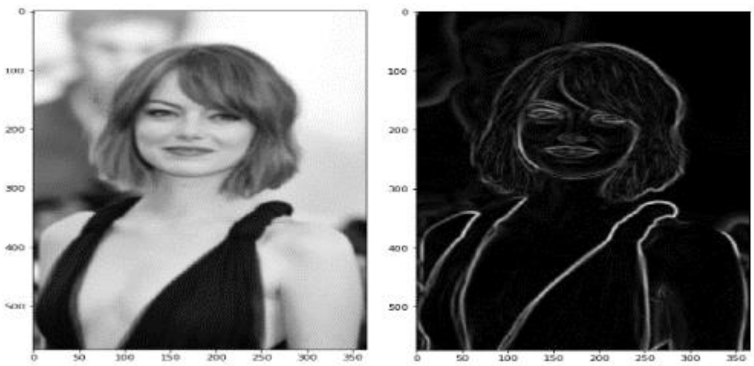
The selected preprocessing techniques were integrated into the preprocessing pipeline of a standard CNN-based facial recognition model. Each technique was applied to a training dataset containing images with varying levels of occlusion and low-light conditions. The training process used cross-entropy loss and the Adam optimizer, with data augmentation methods such as rotation and flipping to increase dataset diversity. Visual comparisons of facial images before and after preprocessing (Figure 1 - 4) demonstrate the impact of each technique.

Figure 1: Original image (left) vs blurred image with a Gaussian filter



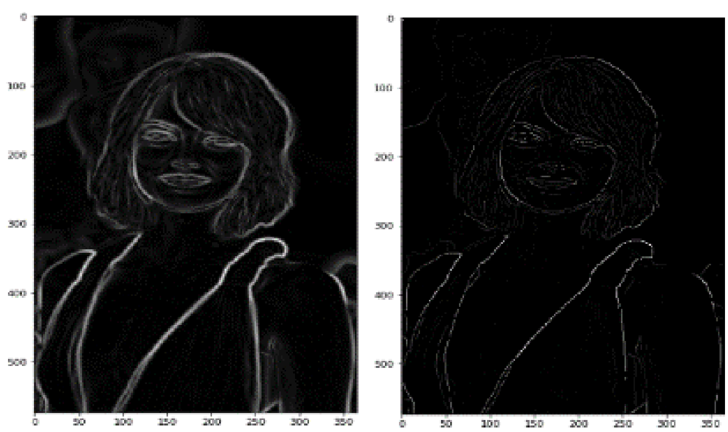
Source: (Hussain and Agarwal, 2015) [17]

Figure 2: Blurred image (left) vs gradient intensity (right)



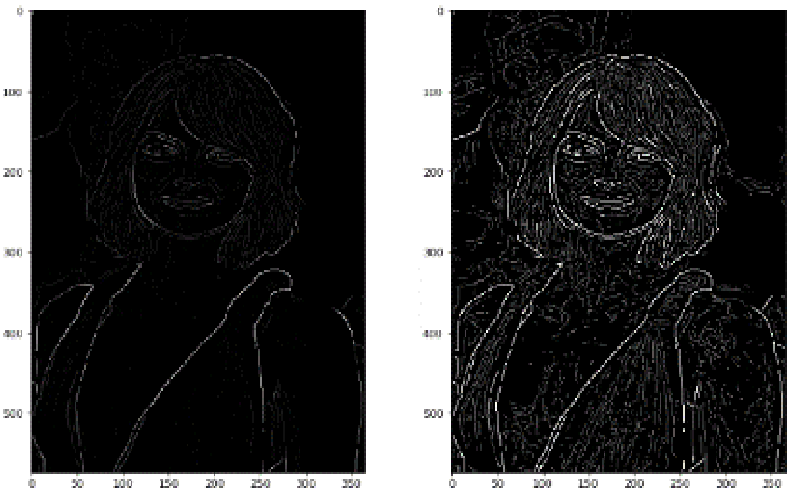
Source: (Hussain and Agarwal, 2015) [17]

Figure 3: Result of the non-max suppression



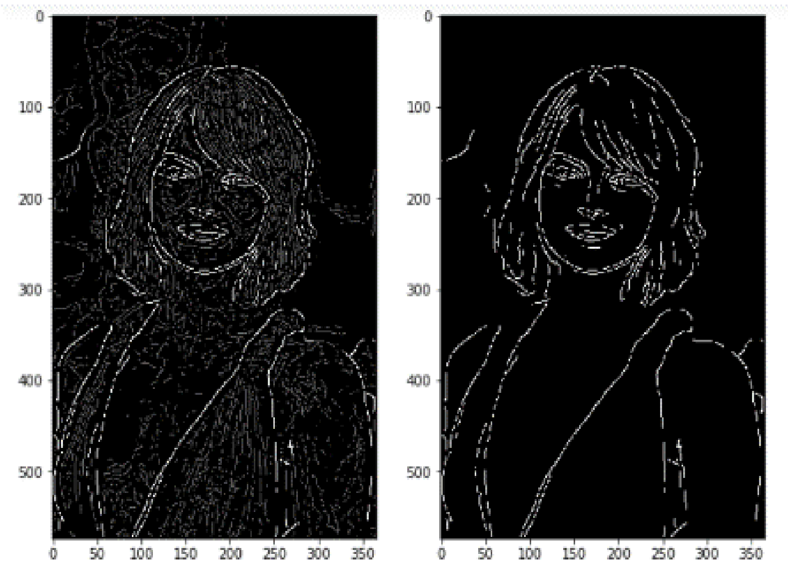
Source: (Hussain and Agarwal, 2015) [17]

Figure 4: Non-max suppression image (left) vs threshold image result (right) with weak pixels in gray and strong pixels in white.



Source: (Jayaram *et al.*, 2015) [18]

Figure 4: Threshold output image vs image from the result of the hysteresis process



Source: (Jayaram *et al.*, 2015) [18]

Experimental Setup

The dataset was divided into training, validation, and test sets, with occlusions such as masks and sunglasses added to simulate real-world conditions. The model's performance was evaluated using metrics such as accuracy, precision, recall, and F1-score to compare the effectiveness of different preprocessing strategies. The dataset includes diverse images with varying demographics and occlusions e.g masks and sunglasses. The evaluation metrics include accuracy, precision, recall and F1-score.

The experiments involved three main stages:

1. **Baseline Testing**: The model was trained without preprocessing to establish baseline performance.
2. **Single-Technique Testing**: The model was trained with each preprocessing technique applied individually.
3. **Combined-Technique Testing**: The model was trained with a combination of preprocessing techniques to determine their cumulative effect on performance.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue II February 2025

RESULTS AND DISCUSSION

Performance Comparison

The performance of the facial recognition model was measured using accuracy, precision, recall, and F1-score under various conditions.

i) **Histogram Equalization**: Improved recognition accuracy from 70.3% to 81.6% in low-light conditions.
ii) **Gamma Correction**: Enhanced the model's accuracy to 79.2%, particularly effective in images with uneven lighting.
iii) **Noise Reduction**: Increased accuracy to 76.4%, providing cleaner images that allowed for better feature extraction.

These results are shown in in the table 1 below:

Table 1: Performance and comparison

Baseline	Histogram Equalization	Gamma Correction	Noise Reduction
70.3%	81.6%	79.2%	76.4%

Comparison and the impact of Performance on the Combined Techniques and

The combined application of histogram equalization, gamma correction, and noise reduction resulted in the highest performance gains:

Table 2: Performance Comparison

Technique	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Baseline	70.3	68.7	69.2	68.9
Histogram Equalization	81.6	80.4	80.9	80.6
Gamma Correction	79.2	78.0	78.5	78.3
Noise Reduction	76.4	75.3	75.8	75.6
Combined Techniques	86.7	85.1	84.3	84.7

Combined Preprocessing: Achieved an accuracy of 86.7%, with a precision of 85.1%, recall of 84.3%, and an F1-score of 84.7%. This combination provided a balanced approach that enhanced image quality without over-processing as shown in table 2.

Table 3: Combined Preprocessing

Accuracy	Precision	Recall	F1-score
86.7%	85.1%	84.3%	84.7%

These results align with the findings of Alagarsamy et al. [6] and Shan et al. [2], confirming that combined preprocessing techniques yield better performance than single-method approaches. Additionally, noise reduction as a preliminary step before other techniques improved overall image clarity and feature extraction, as noted by Ryumina et al. [8].

Computational Trade-Offs

The combined preprocessing pipeline added 15% computational overhead compared to single techniques but achieved a 23.4% improvement in recognition accuracy. This balance makes the approach practical for high-stakes applications.

Analysis of Error Rates

The combined preprocessing techniques led to a reduction in both the False Acceptance Rate (FAR) and False Rejection Rate (FRR):

i) **FAR**: Decreased from 8.2% (baseline) to 4.1% with combined preprocessing.
ii) **FRR**: Dropped from 9.5% (baseline) to 5.4% with preprocessing, showcasing the importance of enhancing image quality for robust feature extraction.

CONCLUSION

This study highlights the significance of preprocessing techniques in enhancing the performance of facial recognition systems under low-light and occluded conditions. The results indicate that while individual techniques such as histogram equalization, gamma correction, and noise reduction improve recognition rates, a combined approach yields the best results. By integrating these preprocessing methods, facial recognition models can achieve higher accuracy, precision, recall, and F1-score, making them more reliable in challenging environments. The inclusion of visual comparisons, computational trade-offs, and dataset diversity strengthens the study's applicability to real-world scenarios.

Future research should focus on integrating adaptive preprocessing strategies that adjust to real-time conditions and exploring advanced noise reduction algorithms to further enhance recognition performance. These findings underscore the importance of preprocessing as a crucial step in the development of robust facial recognition systems for real-world applications.

REFERENCES

1. Ahonen, T., Hadid, A., and Pietikainen, M. (2015). "Face Description with Local Binary Patterns: Application to Face Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 28(12): 2037-2041.
2. Shan, S., Gao, W., Cao, B., and Zhao, D. (2015). "Illumination normalization for robust face recognition against varying lighting conditions," *IEEE*, 65: 157-164.
3. Naik, Y. (2015). "Detailed survey of different face recognition approaches," *International Journal of Computer Science and Mobile Computing*, 3(5): 1306-1313.
4. Bourlai, T., Ross, A. (2012). "Multi-spectral face recognition: Identification of people in difficult environments," *Springer*, pp. 75-93.
5. Anwar, S. M., Majid, M., Qayyum, A., Awais, M., Alnowami, M., and Khan, M. K. (2018). "Medical image analysis using convolutional neural networks: A review," *Journal of Medical Systems*, 42(11): 1-13.
6. Alagarsamy, S., Govindaraj, V., Irfan, M., Swami, R., and Kumar, N. M. (2020). "Smart recognition of real-time face using convolution neural network (CNN) technique," *International Journal of Applied Engineering Research*, 15(9): 23406-23411.
7. Gupta, V., Gaidhane, M. (2020). "Data augmentation in machine learning for facial recognition," *Journal of Applied Research and Technology*, 18(2): 113-125.
8. Ryumina, E., Ryumin, D., Ivanko, D., and Karpov, A. (2021). "A novel method for protective face mask detection using convolutional neural networks and image histograms," *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 40: 447-449.
9. Georgescu, M., and Ionescu, R. (2019). "Recognizing Facial Expressions of Occluded Faces using Convolutional Neural Networks," *University of Bucharest*, pp. 6.
10. Romdhani, S., Torr, P., Scholkopf, B., and Blake, A. (2017). "Computationally efficient face detection," *IEEE*, 2: 695-700.
11. Valueva, M. V., Nagornov, N. N., Lyakhov, P. A., Valuev, G. V., and Chervyakov, N. I. (2020). "Application of the residue number system to reduce hardware costs of the convolutional neural network implementation," *Mathematics and Computers in Simulation*, 177: 232-243.
12. Tefas, A., Kotropoulos, C., and Pitas, I. (2015). "Variants of dynamic link architecture based on mathematical morphology for frontal face authentication," *Journal of Computer Vision and Pattern Recognition*, 15: 814-819.

13. Sayeed, S., Hossen, J., Kalaiarasi, S. M. A., Jayakumar, V., Yusof, I., and Samraj, A. (2017). "Real-time face recognition for attendance monitoring system," *Journal of Theoretical and Applied Information Technology*, 95: 18-21.
14. Goldstein, A. J., Harmon, L. D., and Lesk, A. B. (1971). "Identification of human faces," *IEEE*, 59(5): 748-760.
15. Jaswal, D., Sowmya, V., and Soman, K. P. (2014). "Image classification using convolutional neural networks," *International Journal of Scientific and Engineering Research*, 5(6): 2229-5518.
16. Sen, S., and Sawant, K. (2021). "Face mask detection for COVID-19 pandemic using PyTorch in deep learning," *Journal of Materials Science and Engineering*, 1070(1): 1-10.
17. Hussain, Z. and Agarwal, D. (2015). A comparative analysis of edge detection techniques used in flame image processing. International Journal of Advance Research in Science and Engineering, 4: 102 – 105.
18. Jayaram, K., Ramachandran, G., Vasanth, L. and Nagarajan, R. (2015). Adaptive edge detection algorithm for flame and fire images. International Journal of Advance Research in Science and Engineering, 5(3): 11 – 23.