

ENHANCING FACIAL RECOGNITION ACCURACY IN LOW-LIGHT ENVIRONMENTS USING NEURAL NETWORKS

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Article history:		Abstract:
Received: Accepted:	24 th October 2024 20 th November 2024	Facial recognition technology has become a cornerstone in various applications, ranging from personal device authentication to advanced surveillance systems. However, maintaining accuracy under low-light conditions remains a critical challenge. This study explores innovative neural network techniques, such as the Deep Retinex Decomposition Network (DRDN), CenterFace, and RetinaFace, to enhance recognition accuracy in low-light scenarios. By leveraging datasets like DARKFACE and LOL, this research demonstrates how state-of-the-art image enhancement, feature fusion, and detection algorithms can mitigate the challenges of poor lighting and feature obscuration. Detailed implementation strategies, including dataset preparation, preprocessing, and hybrid model architectures, are discussed. Experimental results show significant improvements in recognition accuracy, noise reduction, and computational efficiency, paving the way for more reliable and versatile facial recognition systems across applications such as security, healthcare, and consumer electronics.

Keywords: Facial recognition 1, low-light environments 2, neural networks 3, DRDN 4, DARKFACE dataset 5, image enhancement 6, feature fusion 7, computational efficiency 8, privacy 9, bias mitigation 10.

1. INTRODUCTION

Facial recognition has evolved into a crucial technology across various domains, including security systems, healthcare, and consumer devices. The capability to recognize individuals based on facial features has opened avenues for enhanced security, streamlined user authentication, and personalized user experiences. However, as adoption increases, so does the need for systems that can reliably operate under diverse environmental conditions.

One of the most significant challenges for facial recognition systems is maintaining accuracy in low-light environments. Poor lighting obscures critical facial features, reduces image quality, and increases the likelihood of false negatives. This issue is especially critical in surveillance scenarios, such as nighttime monitoring, where inadequate illumination leads to unreliable detections. Addressing this challenge requires a combination of advanced algorithms, robust datasets, and innovative preprocessing techniques.

This paper delves into the potential of neural networks, specifically focusing on their role in enhancing recognition performance under low-light conditions. Leveraging state-of-the-art models, datasets like DARKFACE and LOL, and advanced image enhancement techniques, this study aims to address critical challenges and propose scalable solutions for real-world applications. The research also emphasizes the importance of ethical considerations, including bias mitigation and privacy safeguards, to ensure responsible deployment.

2.MATERIAL AND METHOD

The Challenge of Low-Light Environments

Low-light environments present a unique set of challenges for facial recognition systems. Reduced illumination diminishes the visibility of critical features, such as the eyes, nose, and mouth, which are essential for accurate recognition. Traditional algorithms often struggle in such conditions, leading to increased false negatives and reduced reliability.

For instance, experiments using the DARKFACE dataset—a benchmark dataset specifically designed for low-light image processing—highlight the limitations of conventional approaches. These methods frequently fail to preserve essential details, such as facial contours and texture, which are critical for accurate detection.



Advanced methods, like Deep Retinex Networks, aim to overcome these limitations by enhancing image quality and preserving feature integrity. In controlled trials, these networks have demonstrated recognition accuracies of up to 85%, a significant improvement over traditional methods.

To address these challenges comprehensively, this study focuses on the integration of neural networks with image enhancement techniques tailored for lowlight environments. These approaches aim to restore image quality, enhance feature visibility, and reduce noise, thereby improving overall system performance.

State-of-the-Art Techniques

Image Enhancement Using Neural Networks -Advanced neural networks are pivotal in enhancing image quality under low-light conditions. Two notable examples include:

- Deep Retinex Decomposition Network (DRDN): Inspired by the human visual system, DRDN decomposes images into illumination and reflectance components. This separation allows for effective restoration of details while preserving facial features critical for recognition.
- **Deep Lightening Network (DLN):** This model focuses on brightening images and reducing noise through adaptive learning. It employs techniques like histogram equalization and contrast enhancement to improve feature visibility.

Advanced Detection Algorithms - Efficient detection algorithms play a crucial role in ensuring the reliability of facial recognition systems in low-light settings:

- RetinaFace: Combines facial detection and landmark localization, achieving high precision even under challenging lighting conditions.
- Two-Step Faster R-CNN: Adopts a sequential approach, first detecting body regions and

 then focusing on facial features to enhance accuracy while minimizing computational overhead.

Feature Fusion and Noise Reduction - Feature fusion and noise reduction are essential for robust recognition in low-light conditions. Techniques like multi-scale feature fusion integrate information from various resolutions, preserving spatial context and enhancing discriminative power. Denoising layers selectively filter noise while retaining critical details, ensuring accurate feature extraction. Algorithms like CenterFace effectively combine these techniques, enabling robust facial recognition.

Implementation Framework

Step 1: Dataset Preparation - Diverse datasets, such as DARKFACE and LOL, are essential for training and validating models. These datasets include images captured under various lighting conditions, providing a comprehensive training ground. However, biases in these datasets—such as underrepresentation of certain demographic groups—pose challenges to generalizability. To address these issues, data augmentation techniques, synthetic data generation, and targeted diversification are employed.

Step 2: Image Preprocessing - Preprocessing involves several critical steps:

- **Resizing and Normalization:** Images are resized to a uniform resolution (e.g., 224x224 pixels) and normalized to ensure consistency.
- Histogram Equalization: Enhances contrast and feature visibility, particularly in low-light images.
- Augmentation: Techniques like random rotations, horizontal flips, and brightness adjustments improve dataset diversity.









Figure 2. "A side-by-side comparison of a raw input image and its preprocessed counterpart vividly illustrates the impact of resizing, normalization, and histogram equalization, showcasing improved clarity and uniformity essential for effective model training."

Step 3: Model Architecture - A hybrid framework combining DRDN and CenterFace is employed to enhance performance. DRDN focuses on image enhancement, while CenterFace integrates feature fusion and denoising layers for robust detection.

Step 4: Training and Optimization - Models are trained using pre-trained architectures, such as ResNet or VGG, fine-tuned for low-light conditions. **3. RESULTS**

Optimization techniques, including learning rate scheduling and early stopping, ensure robust performance.

Step 5: Evaluation - Evaluation metrics include accuracy, precision, recall, and F1-score. Statistical significance tests are conducted to validate improvements over baseline methods.





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Figure 4. Illustrates the enhancement in preserving facial features, increasing from 60% to 90%.



Figure 5. Highlights a significant improvement in computational efficiency, with scores rising from 50% to 80%.

4. DISCUSSION

Applications and Future Directions

The enhanced facial recognition system has vast applications, including:

• Security and Surveillance: Reliable identification in low-light settings improves crime prevention and response.

• Healthcare: Accurate patient identification during emergency scenarios.

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• Consumer Electronics: Robust device authentication under diverse lighting conditions.

Future work could explore multi-modal data integration, such as combining thermal imaging with visual data, to further enhance recognition capabilities. Multi-modal integration faces challenges such as aligning thermal and visual data streams, which may have different spatial resolutions and temporal sampling rates. Calibration of sensors to ensure data consistency and eliminating noise from each modality are critical steps. For example, studies have shown that combining thermal imaging for temperature profiles with visual textures improves detection in low-light and occluded environments, but managing the increased computational burden requires optimized algorithms and hardware accelerators like FPGAs or TPUs. Successfully addressing these issues could result in more robust and adaptable facial recognition systems. Integrating these modalities requires advanced alignment techniques to synchronize disparate data sources. For instance, thermal imaging can capture heat signatures independent of lighting, while visual data provides detailed textures. Challenges include ensuring temporal and spatial coherence between modalities, addressing sensor calibration issues, and managing increased computational requirements. Despite these obstacles, such integration could significantly improve system robustness, particularly in scenarios with extreme lighting variations or occlusions.

5. CONCLUSIONS

Neural networks, when combined with advanced image enhancement and detection algorithms, can significantly improve facial recognition accuracy in lowlight environments. However, these advancements raise critical ethical considerations, such as the potential misuse of facial recognition technologies for unauthorized surveillance or privacy violations. To address these concerns, it is essential to implement safeguards like data encryption, transparency in usage policies, and regulatory oversight. Additionally, ensuring that these systems are used responsibly within ethical frameworks can help mitigate risks associated with surveillance overreach. Techniques like DRDN and CenterFace demonstrate the potential of AI to overcome traditional limitations, paving the way for more reliable and adaptable biometric systems. Continued innovation in this domain promises to make facial recognition technology even more robust and versatile, addressing challenges across a spectrum of real-world applications.

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