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A Novel Domain Adaptation-Based Framework for Face Recognition under Darkened and Overexposed Situations

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ABSTRACT

Face recognition has become a cornerstone technology in various domains, including security, healthcare, and personalized applications. While traditional methods relied on handcrafted features and classical machine learning, advancements in deep learning have significantly improved face recognition's accuracy and robustness. However, challenges such as environmental variations—darkened or overexposed images—create domain shifts that compromise the generalization of these models. To address this, domain adaptation techniques have emerged as a promising solution, aligning feature distributions between source domain and target domain. This paper proposes a domain adaptation framework integrating Correlation Alignment (CORAL) and a Residual Network (ResNet) to enhance model robustness under varying conditions. Our method effectively reduces domain discrepancies using CORAL loss. Experimental results demonstrate that domain adaptation significantly improves model performance, as evidenced by reduced Equal Error Rates (EER) and enhanced feature alignment in challenging lighting scenarios. Despite its success, domain adaptation faces challenges such as computational costs and handling extreme distortions, highlighting the need for further research into more efficient and generalized approaches.

Keywords: Face recognition; Deep learning; Domain adaptation

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1. Introduction

Face recognition is a critical technology in computer vision that involves identifying or verifying the identity of individuals using their facial features [1, 2]. Over the years, it has gained immense attention and has been widely applied in various fields, including security, access control, social media tagging, personalized marketing, and even health-care [3–6]. Its ability to enhance convenience and improve security systems has made it a cornerstone of many modern technological applications.

Traditionally, face recognition relied on handcrafted features and classical machine learning algorithms [7–10]. These methods typically involved extracting specific facial landmarks or descriptors, such as the distance between the eyes or the shape of the jawline, to distinguish between individuals. Popular algorithms, such as Principal Component Analysis (PCA) [11, 12] and Linear Discriminant Analysis (LDA) [13, 14], were used to project facial data onto lower-dimensional spaces for classification tasks. Although effective in controlled environments, these traditional approaches often struggled in real-world scenarios [15–17]. They were highly sensitive to variations in lighting, pose, facial expressions, and occlusions. As a result, their accuracy and robustness were significantly compromised in uncontrolled settings.

The advent of artificial intelligence (AI) [18–20], particularly deep learning [21–23], revolutionized the field of computer vision. For example, Xiong et al. proposed a deep learning-based multifunctional end-to-end model that integrates denoising and character classification to enhance the efficiency and accuracy of Optical Character Recognition (OCR) [24]. AI-based face recognition systems leverage deep neural networks to automatically extract hierarchical and discriminative features from facial images. Convolutional Neural Networks (CNNs) [25–27], for instance, have become the backbone of many state-of-the-art face recognition models. These networks can handle complex variations in facial data, making them highly effective in diverse and challenging environments. Popular AI-based frameworks like FaceNet, DeepFace, and ArcFace [28–30] have achieved remarkable accuracy in large-scale datasets, setting new benchmarks for the field. However, even with the advancements brought by AI, face recognition systems are not immune to challenges. Environmental factors, such as lighting conditions and camera exposure, can significantly degrade the quality of facial images. For example, an overexposed image may wash out important facial details, while an underexposed image may obscure critical features. Such issues create a domain shift between the training data (typically captured under ideal conditions) and the test data (often captured in less controlled settings). This domain shift adversely affects the performance and generalization ability of face recognition models.

To address these challenges, the concept of domain adaptation has emerged as a promising solution [31–33]. Domain adaptation is a subfield of transfer learning that focuses on reducing the domain discrepancy between the source domain (training data) and the target domain (test data). By aligning the feature distributions of the two domains, domain adaptation techniques improve the generalization ability of models across varying environments. Over the years, several domain adaptation methods have been proposed, such as adversarial training, moment matching, and feature alignment. These methods have been successfully applied in various applications, including image classification, object detection, and, more recently, face recognition.

In this paper, we aim to apply domain adaptation to enhance the robustness and generalization ability of face recognition models under challenging conditions. Specifically, we focus on addressing the issues caused by overexposure and underexposure in facial images. Our approach leverages a CNN backbone to extract fixed-length feature vectors from facial images across different exposure conditions for matching. To ensure the alignment of feature distributions between domains, we employ Correlation Alignment (CORAL) loss [34], which minimizes the discrepancy between the second-order statistics of source and target features. Additionally, cross-entropy loss is used to optimize the classification performance of the model. The framework of our method is illustrated in **Figure 1**. First, facial images from the source domain (original faces) and the target domain (darkened or overexposed faces) are passed through a shared CNN backbone. The CNN extracts fixed-length feature vectors for each image. These feature vectors are then used for two purposes: classification and feature alignment. For classification, cross-entropy loss ensures the correct identification of individuals in the source domain. For feature alignment, CORAL loss is applied to reduce the domain gap between the source and target domains, improving the model's ability to recognize faces in diverse exposure conditions.

The key contribution of this paper lies in the integration of domain adaptation into face recognition to handle environmental variations, such as lighting and exposure. By aligning feature distributions across domains, our approach enhances the adaptability and reliability of face recognition models. This work not only addresses the limitations of traditional and AI-based face recognition methods but also demonstrates the potential of domain adaptation in improving the generalization of machine learning models in real-world scenarios.

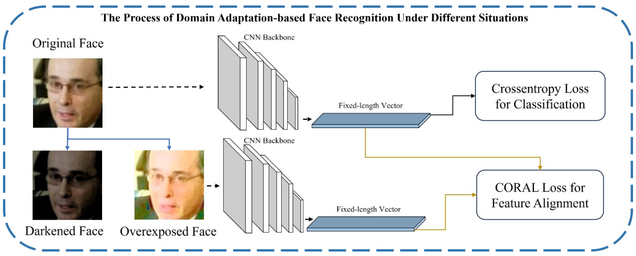

Figure 1. The architecture of the proposed domain adaptation-based fingerprint recognition framework.

2. Literature Review

2.1. Face recognition

Facial recognition has been a key research focus for several decades [35–37], transitioning from traditional methods to modern deep learning-based approaches due to technological advancements across various domains [38–40]. Early techniques relied on handcrafted feature extraction, which, while straightforward, provided the groundwork for later developments. Turk and Pentland introduced the use of Principal Component Analysis (PCA) for facial recognition [41], coining the term Eigenfaces to facilitate dimensionality reduction and feature extraction. However, PCA-based methods proved highly sensitive to changes in lighting, pose, and facial expressions. To mitigate these issues, researchers developed Linear Discriminant Analysis (LDA) and Local Binary Patterns (LBP) [42, 43], which offered improved robustness to specific variations but still depended on manually engineered features. The emergence of deep learning transformed facial recognition by enabling automatic feature extraction from raw images. Taigman et al. introduced DeepFace [44], an early deep learning model for face recognition that utilized a deep neural network to achieve near-human accuracy. Schroff et al. advanced this with FaceNet [28], which employed a triplet loss function to learn a compact embedding space for both recognition and clustering tasks. The adoption of deep embeddings greatly improved the scalability and precision of facial recognition systems.

2.2. Domain adaptation

Domain adaptation techniques can be broadly divided into two main categories based on their architectures: shallow and deep. Shallow domain adaptation methods [45, 46] primarily use instance-based or feature-based approaches to align domain distributions. These methods aim to minimize domain discrepancies by leveraging metrics such as maximum mean discrepancy (MMD), Wasserstein distance, correlation alignment (CORAL), Kullback-Leibler (KL) divergence [47, 48], and contrastive domain discrepancy (CDD). On the other hand, deep domain adaptation techniques utilize neural network architectures [49, 50], including convolutional networks, autoencoders, and adversarial models, to address domain shifts. These approaches often integrate distance metrics at various layers within dual-network setups, where one network processes source domain data and the other processes target domain data. By comparing feature representations across corresponding layers, these methods effectively reduce domain discrepancies.

3. Method

3.1. Dataset preparation

The dataset utilized in this study is obtained from Kaggle and comprises a total of 1,105 images, representing 248 distinct individuals, including both male and female participants. The images are in RGB format, with each individual having varying numbers of images, though no individual is represented by more than 10 samples. Each image is originally provided at a resolution of 160x160 pixels. For the purposes of training and evaluation, 70% of the dataset is allocated to the training set, while the remaining 30% is reserved for testing. To simulate conditions of darkened and overexposed images, brightness adjustments were applied to the original images by systematically altering pixel intensity values. Specifically, pixel values were either increased to simulate overexposure or decreased to create darkened effects, mimicking real-world scenarios with challenging lighting conditions. This controlled adjustment ensured the creation of visually distinct variations while preserving the overall structure of the facial features. A selection of sample images from the dataset, along with their processed counterparts, is shown in **Figures 2–4**

Figure 2. The face samples from the original dataset.

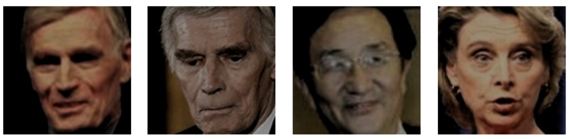

Figure 3. The face samples under the darkened situation.

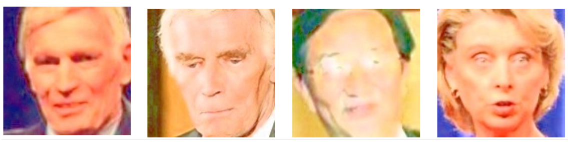

Figure 4. The face samples under the overexposed situation.

3.2. Domain adaptation-based face recognition

a) *Preliminaries of domain adaptation*

Domain adaptation is a subfield of machine learning that focuses on addressing the challenge of domain shift, where the source domain and the target domain come from different distributions. This shift can significantly degrade model performance, as most machine learning algorithms assume identical data distributions across training and testing phases. Domain adaptation techniques aim to bridge this gap by aligning the source and target domain distributions, enabling models to generalize effectively to unseen or challenging conditions. Methods for domain adaptation can broadly be categorized into shallow and deep approaches. Shallow methods often rely on feature transformation techniques, such as minimizing metrics like Maximum Mean Discrepancy (MMD) or Correlation Alignment (CORAL), to reduce discrepancies between domains. These approaches focus on aligning feature-level representations without leveraging the full potential of deep learning. In contrast, deep domain adaptation methods utilize neural networks to learn domain-invariant features. These techniques often incorporate adversarial training, where a domain discriminator tries to distinguish between the source and target domains, while the feature extractor aims to confuse the discriminator, promoting alignment. Other approaches, such as adding specific loss functions to measure domain similarity, further enhance feature alignment.

b) *CORAL-based ResNet framework*

The proposed CORAL-based ResNet framework integrates Correlation Alignment (CORAL) and the Residual Network (ResNet) to tackle domain adaptation challenges by aligning feature distributions and improving feature extraction capabilities. In the CORAL-based ResNet framework, ResNet acts as the feature extractor, leveraging its deep residual blocks to generate robust feature representations from input data. CORAL loss is then applied to these feature representations to align the distributions of source and target domains. This combination ensures both high-quality feature extraction and effective domain adaptation, making the framework suitable for tasks like image classification, object detection, and face recognition in diverse environments.

CORAL is a domain adaptation technique that focuses on aligning the second-order statistics (covariance) of source and target domain feature representations. Unlike adversarial approaches that require training a domain discriminator, CORAL achieves feature alignment by directly minimizing the distance between covariance matrices of the two domains. This is often achieved using a loss function that calculates the Frobenius norm of the difference between the covariance matrices of the source and target features. By reducing this discrepancy, CORAL helps models learn domain-invariant features without explicitly needing labeled data in the target domain. Its simplicity and effectiveness make it a popular choice for feature alignment in domain adaptation tasks.

ResNet is a deep neural network architecture known for its ability to train very deep networks effectively. The key innovation of ResNet lies in its residual blocks, which introduce skip connections that bypass one or more layers. These skip connections address the vanishing gradient problem by allowing gradients to flow directly through the network during backpropagation, ensuring that deeper layers continue to learn effectively. ResNet architectures have become a cornerstone of image classification and feature extraction tasks due to their high performance and scalability. Variants like ResNet-50 and ResNet-101 are widely used in both research and real-world applications.

c) *Hyperparameter setting*

The Adam optimizer was utilized for parameter adjustment, benefiting from its adaptive learning rate and consistent performance across diverse machine learning tasks. The training process spanned 20 epochs with a batch size of 8, striking a balance between computational resource usage and effective model convergence. To assess the model's effectiveness, the Equal Error Rate (EER) was employed as a primary evaluation metric [49], supplemented by the Receiver Operating Characteristic (ROC) curve for a detailed performance analysis. EER is particularly significant in biometric systems, as it identifies the point where the false acceptance rate (FAR) matches the false rejection rate (FRR). This metric provides a concise representation of the trade-off between these two error types, serving as an essential indicator of the system's reliability. A lower EER signifies higher accuracy and robustness, underscoring the model's potential for real-world fingerprint recognition applications. Additionally, the ROC curve offers a complementary perspective by graphically depicting the model's performance across various decision thresholds.

4. Experimental results and discussion

4.1. The performance of face recognition

Figure 5 and **Table 1** provide the performance of the model on three different datasets: the original dataset, the darkened dataset, and the overexposed dataset. Each dataset's performance is evaluated using the ROC curve and the EER. These metrics provide insights into the model's classification capabilities under varying conditions. The first ROC curve corresponds to the model's predictions on the original dataset. With an EER of 0.3488, this result reflects the baseline performance of the model when tested on images without significant alterations. The relatively low EER indicates that the model is capable of distinguishing between classes with moderate accuracy. However, this baseline highlights that the model still encounters challenges, likely due to intra-class variations and inter-class similarities in the original data. The second ROC curve depicts the model's performance on the darkened dataset. The EER increases to 0.4137, indicating a drop in model accuracy under darkened conditions. This decline can be attributed to the loss of critical facial details in images with reduced brightness. Darkened images obscure fine-grained features, such as contours and textures, which are essential for accurate classification. Consequently, the model struggles to effectively extract discriminative features, leading to increased false acceptance and rejection rates. The third ROC curve represents the model's predictions on the overexposed dataset, with an EER of 0.4523. This is the highest EER among the three datasets, signifying the most significant degradation in performance. Overexposed images suffer from excessive brightness, causing key facial features to be washed out or entirely lost. This lack of discernible details makes it difficult for the model to correctly classify images, resulting in higher error rates. The results highlight the sensitivity of face recognition models to variations in lighting conditions. The increased EER values for both the darkened and overexposed datasets underscore the challenges posed by environmental factors. In both cases, the primary issue lies in the disruption of feature extraction. Darkened images obscure critical features, while overexposed images erase or distort them. These disruptions create a domain shift between the training data (original dataset) and the test data (altered datasets), reducing the model's ability to generalize.

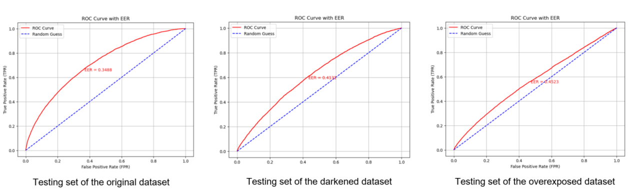

Figure 5. The EER comparison under different conditions using direct prediction.

Figure 6 further presented the similarity scores for both same-identity and different-identity pairs of some samples.

For the original dataset, same-identity pairs achieve a high similarity score of 0.92, indicating that the model effectively recognizes individuals under ideal lighting conditions. For different-identity pairs, the similarity score is relatively low at 0.73, demonstrating the model's capability to differentiate between distinct individuals. These scores serve as the baseline for comparison with altered datasets. In the darkened dataset, the similarity score for same-identity pairs drops to 0.88. This reduction is likely due to the obscured facial details in darker images, which challenge the model's ability to extract distinguishing features. More notably, the similarity score for different-identity pairs decreases significantly to 0.66. This indicates a decline in the model's ability to differentiate between different individuals. The reduction arises because darkened images often lose detailed facial textures and contours, leading to less distinctive representations. In the overexposed dataset, the similarity score for same-identity pairs is 0.86, slightly lower than the darkened dataset.

Table 1. The numerical EER comparison under different conditions using direct prediction.

Model	EER
Direct prediction on testing set of the original dataset	0.3488
Direct prediction on testing set of the darkened dataset	0.4131
Direct prediction on testing set of the overexposed dataset	0.4523

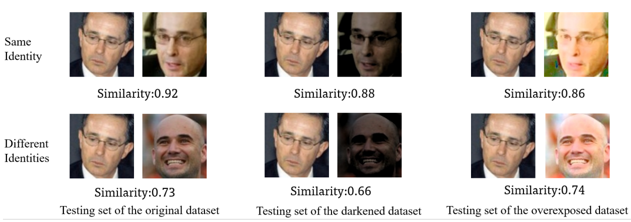

Figure 6. The prediction samples under different conditions.

Figure 7 and **Table 2** illustrate a clear performance improvement when domain adaptation is applied compared to direct prediction on both the darkened and overexposed datasets. In the darkened dataset, the Equal Error Rate (EER) for direct prediction is 0.4137, indicating the model struggles with distinguishing between classes due to the loss of critical features in darker images. After applying domain adaptation, the EER is reduced to 0.3677, demonstrating a significant improvement. This reduction highlights the effectiveness of domain adaptation in aligning feature distributions between the source (original) and target (darkened) domains, enabling the model to generalize better under challenging conditions. Similarly, for the overexposed dataset, the EER drops from 0.4523 in direct prediction to 0.3842 with domain adaptation. The improvement indicates that domain adaptation effectively mitigates the impact of overexposure by learning domain-invariant features. While overexposed images erase important facial details, the alignment provided by domain adaptation helps the model maintain a more robust decision boundary. In addition, the samples in **Figure 8** further highlights the effectiveness of domain adaptation in improving similarity scores for both same-identity and different-identity pairs on darkened and overexposed datasets.

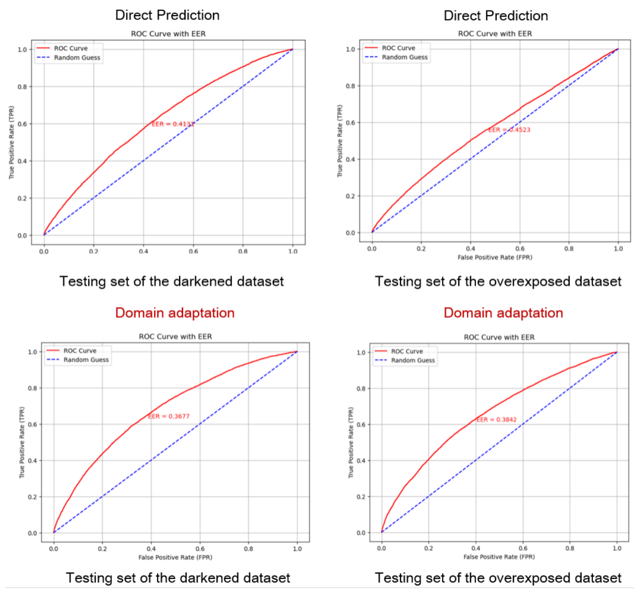

Figure 7. The EER comparison between direct prediction and domain adaptation-based prediction under different conditions.

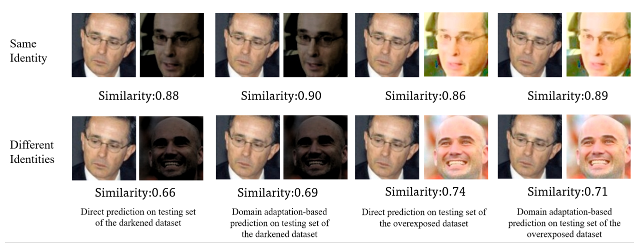

Figure 8. The comparison of prediction samples using direct prediction and domain adaptation-based prediction.

As shown in **Figure 9**, for the darkened face, the heatmaps generated from direct prediction focus less effectively on facial regions, with dispersed attention that misses critical features. In contrast, the heatmap from domain adaptation-based prediction shows more concentrated attention on key facial areas, indicating improved feature

Table 2. The numerical EER comparison between direct prediction and domain adaptation-based prediction under different conditions.

Model	EER
Direct prediction on testing set of the darkened dataset	0.4131
Direct prediction on testing set of the overexposed dataset	0.4523
Domain adaptation-based prediction on testing set of the darkened dataset	**0.3677**
Domain adaptation-based prediction on testing set of the overexposed dataset	**0.3842**

alignment and robustness under low-light conditions. Similarly, for the overexposed face, direct prediction suffers from a lack of focus on significant facial features due to the washed-out image details. However, domain adaptation enables better feature extraction, as evidenced by the heatmap's sharper focus on critical facial landmarks around eyes and nose.

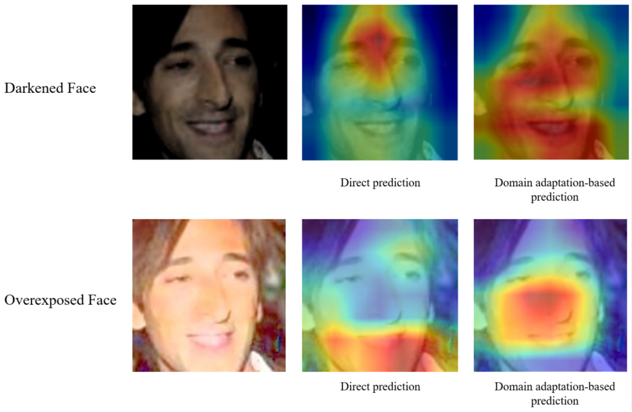

Figure 9. The Grad-CAM visualization of the attention using direct prediction and domain adaptation-based prediction.

4.2. Discussion

While domain adaptation has shown promising results in improving the robustness of face recognition systems under challenging conditions i.e. darkened and overexposed faces, several limitations and challenges remain. First, the effectiveness of domain adaptation heavily depends on the quality and diversity of the source and target domain mappings. Extreme distortions, such as severe overexposure or darkness that obliterates critical facial features, remain a significant challenge. In these cases, the model may struggle to align features effectively due to the irretrievable loss of information, resulting in suboptimal performance. Second, domain adaptation often incurs high computational costs. The alignment of feature distributions, especially in deep neural networks, requires significant resources, which can limit its feasibility for real-time or resource-constrained applications. The added complexity of domain adaptation algorithms may also introduce latency in systems where rapid predictions are critical. Third, the generalization capability of domain adaptation methods is not guaranteed across all scenarios. While these methods address specific domain shifts, they may not be effective in handling other variations, such as changes in pose, occlusion, or background clutter, which are common in real-world settings. Ensuring robustness to a wider range of factors remains a critical area for further investigation. Future research should focus on addressing these challenges by exploring lightweight and efficient domain adaptation techniques that maintain high performance without excessive computational demands. Additionally, incorporating advanced data augmentation strategies to simulate diverse environmental conditions during training could enhance the model's robustness. Investigating unsupervised or semi-supervised methods for domain adaptation may also help reduce reliance on labeled data, making the approach more scalable.

5. Conclusions

This study demonstrates the effectiveness of domain adaptation in improving face recognition performance under challenging environmental conditions, such as darkened and overexposed images. By integrating CORAL-based alignment with ResNet, the proposed framework reduces domain discrepancies, enhancing the model's generalization capabilities. Experimental results confirm significant improvements in recognition accuracy, as shown by lower EERs and enhanced attention mechanisms. However, challenges remain, including the reliance on high-quality domain mappings, computational costs, and limitations in addressing extreme distortions or other variations like pose and occlusions. Future research should focus on developing lightweight and scalable domain adaptation methods, incorporating advanced data augmentation strategies, and exploring semi-supervised approaches to reduce dependency on labeled data. By addressing these limitations, domain adaptation can further solidify its role in making face recognition systems more robust and practical for real-world applications.

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