Iris Super-Resolution for Images Sourced from Websites and Social Media

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Abstract

The iris is a highly distinctive and stable biometric trait widely used in high-security applications. Recent studies have explored iris recognition using ocular images collected from websites and social media. However, ocular images obtained from online sources exhibit significant non-idealities, one of the most critical being their lower resolution compared to images typically used for iris recognition. Super-resolution techniques can potentially enhance iris details and improve recognition performance. Nevertheless, existing studies on super-resolution for iris recognition focus on images acquired under controlled conditions and overlook images collected online. This work is the first to study super-resolution for iris recognition using web and social media images. We propose a transfer learning approach in which deep neural networks are trained on high-quality ocular datasets and then applied to ocular images collected online. Experimental results demonstrate improved recognition accuracy, especially for dark-colored eyes.

Keywords

Biometrics, iris, super-resolution, websites, social media

1. Introduction

Biometric recognition systems are increasingly deployed in cybersecurity applications, as they provide enabling technologies capable of delivering highly accurate and user-friendly identity recognition mechanisms. Among biometric traits, the iris is regarded as one of the most distinctive and stable characteristics. Consequently, iris recognition systems are widely adopted for authentication and identification in critical environments [1].

One of the main limitations of current iris recognition systems lies in the acquisition process, which requires a high level of user cooperation. Individuals are typically asked to remain still at a short distance from the sensor with their eyes fully open. Moreover, the acquisition relies on near-infrared illumination, which some users may perceive as potentially harmful. To improve the usability and accessibility of iris recognition technologies, several studies have demonstrated the feasibility of performing iris recognition from ocular images captured under less controlled and less constrained conditions [2]. Recent research has also shown that iris recognition is feasible using ocular images collected from websites and social media [3]. However, such images generally exhibit lower quality compared to those acquired in more constrained settings [4]. Web-sourced ocular images present a variety of non-idealities, including heterogeneous acquisition artifacts resulting from diverse sensors, uncontrolled environmental factors such as varying illumination and viewing distances, motion blur, and heavy compression. Among these challenges, the low spatial resolution of the ocular region is particularly significant. Indeed, a substantial portion of online images exhibit an iris diameter smaller than 140 pixels, which is commonly regarded as the minimum required for reliable biometric recognition [5].

Super-Resolution (SR) techniques can therefore be used to increase the number of pixels available for biometric recognition and, consequently, improve the overall accuracy of iris recognition methods applied to ocular images collected from websites and social media. SR refers to the computational process of reconstructing a high-resolution image from a low-resolution input. The primary objective

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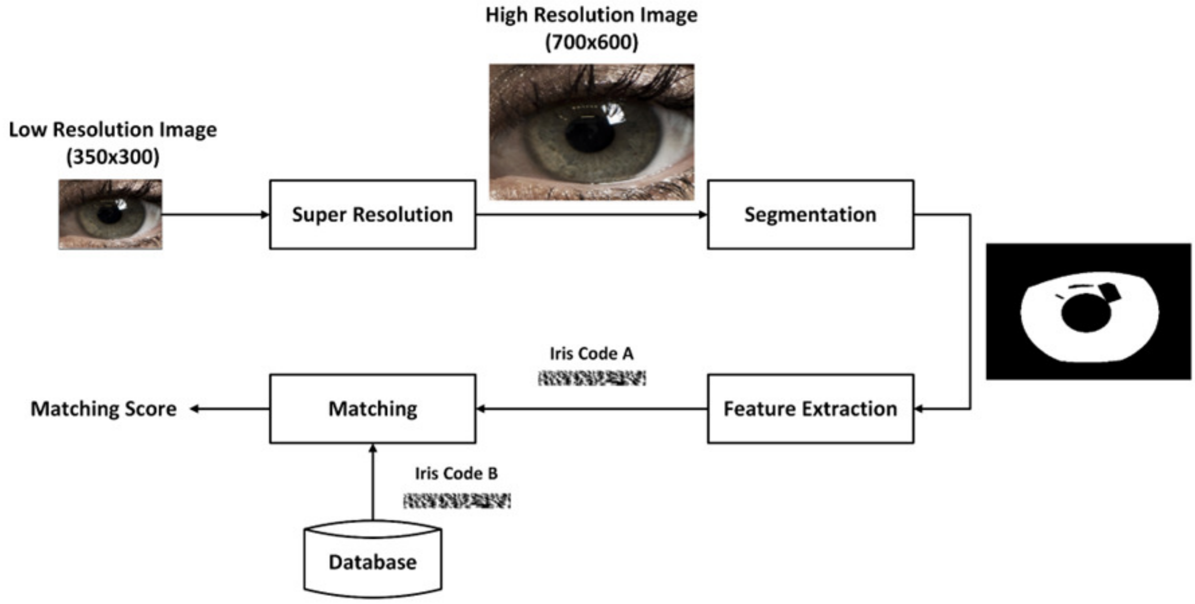

Figure 1: Schema of the iris recognition pipeline integrating a super-resolution module.

of SR methods is to infer and restore the missing high-frequency spatial details (such as fine textures and edges) that are inherently lost during acquisition, downsampling, or degradation [6]. As shown in Figure 1, SR can be integrated into the biometric recognition pipeline to increase the quality of the input sample. However, the existing literature on SR for iris recognition primarily focuses on near-infrared images acquired in controlled settings [7]. Only a few studies have considered images acquired under visible-light conditions [2]. To the best of our knowledge, there are no studies on SR for iris recognition based on ocular images collected from websites and social media.

This paper presents the first study on deep neural networks for SR designed for iris recognition using ocular images collected from websites and social media. A critical constraint in this domain is the inability to employ standard supervised training of SR on web-sourced data, as existing public datasets lack the high-resolution ground truth required for effective model optimization. To address this problem, we propose a method based on transfer learning. We trained different deep neural networks using high-quality ocular images acquired under visible-light conditions and then applied the trained networks to ocular images collected from websites and social media. Specifically, we considered the following SR models: RCAN [8], ESRGAN [9], and Real-ESRGAN [10]. To train the SR models for ocular images acquired in visible light, we used the Hong Kong Polytechnic University Cross-Spectral Iris Images Database [11]. We then analyzed the effect of the trained SR techniques on the identity recognition accuracy of well-known biometric recognition software [12] for both the Hong Kong Polytechnic University Cross-Spectral Iris Images Database and I-SOCIAL-DB [3]. I-SOCIAL-DB is a dataset of ocular images obtained by cropping face portraits sourced from websites and social media. The obtained results are encouraging, demonstrating the benefits of applying SR to challenging ocular images. In particular, the proposed method proved to be especially effective for images depicting dark irises.

The remainder of this paper is organized as follows. Section 2 reviews the related work in iris SR, from algorithmic approaches to modern deep learning models. Section 3 describes our proposed approach, including the selected SR architectures, the biometric recognition framework, and the experimental protocol. Section 4 presents the experimental results. Finally, Section 5 concludes the work.

2. Related Work

SR techniques employed in iris recognition are mostly designed for samples acquired under near-infrared illumination and can be categorized into reconstruction-based methods or single-image methods. Reconstruction-based approaches enhance restoration quality by combining information from multiple low-resolution frames or by explicitly modeling the image formation process [13]. However, these methods typically rely on complex theoretical assumptions and require precise sub-pixel alignment between input images. For this reason, most studies in the literature use a single ocular image as input. Single-image methods can be divided into interpolation algorithms, data-driven approaches, techniques based on Convolutional Neural Networks (CNNs), and techniques based on Generative Adversarial Networks (GANs).

The most commonly used interpolation algorithms are nearest-neighbor, bilinear, and bicubic [14]. While these approaches are computationally efficient, they generally fail to recover the high-frequency texture details essential for biometric recognition. As a result, interpolation can introduce blurring artifacts in the iris pattern. For example, the study presented in [15] shows that interpolation algorithms can decrease the overall iris recognition accuracy.

Data-driven methods learn the mapping function between low-resolution and high-resolution image patches using training pairs and handcrafted features. Several studies have demonstrated the effectiveness of strategies based on machine learning for iris biometrics. In [16], PCA-based eigen-patch reconstruction and neighbor embedding techniques outperform traditional interpolation at very low resolutions. The method described in [17] uses multi-layer perceptron networks to handle different edge types in iris images.

Techniques based on CNNs are more recent than traditional data-driven methods. For example, the study in [18] applied a Very Deep Super-Resolution (VDSR) network to periocular images and investigated transfer learning strategies using models such as SRCNN [19]. However, CNN-based SR models can generate textures that appear realistic but lack the structural integrity necessary for identity recognition tasks [20]. Recent works, such as [21], emphasize the importance of preserving biometric identity rather than focusing solely on visual enhancement.

GAN-based techniques aim to address the limitations of pixel-wise optimization by generating more realistic textures. For instance, the Super-Resolution Generative Adversarial Network (SRGAN) has been applied to near-infrared iris images [22]. Although SRGAN improves perceptual quality, it does not enhance classification accuracy, underscoring the gap between visual fidelity and biometric discriminativeness. To mitigate this limitation, several approaches incorporate identity-preserving losses. For example, IrisDNet [23] employs a densely connected architecture supervised by an identity loss. Moreover, architectures integrating attention mechanisms aim to capture global structures and long-range dependencies. For instance, [24] proposes a hybrid wavelet-based model, and [25] introduces the SwinGIris framework.

Although most SR studies for iris recognition focus on near-infrared images, a few consider cross-spectral illumination conditions. The Ocular Super-Resolution CycleGAN (OSRCycleGAN) [26] modifies the CycleGAN architecture to improve cross-spectral matching for ocular biometrics. Other studies explore conditional GANs to translate images between near-infrared and visible-light domains [27].

While SR models based on deep learning show promising results, their effectiveness has been demonstrated primarily for ocular images acquired under constrained scenarios. Although some research addresses visible-light conditions [28], these datasets typically feature higher resolutions and different degradation characteristics compared to web-sourced images. Existing approaches are not designed to handle the severe and uncontrolled degradation artifacts found in images obtained from websites and social media. To the best of our knowledge, this is the first study addressing the problem of iris SR for biometric recognition using ocular images collected from websites and social media.

3. Methodology

This paper presents a study on SR based on deep neural networks aimed at increasing the quality of iris textures in ocular images collected from websites and social media. Because web-sourced ocular images rarely possess sufficient resolution for training deep neural networks, we fine-tune state-of-the-art SR models using high-resolution ocular images acquired under visible-light and controlled conditions. We then apply the trained networks to ocular images collected from websites and social media and integrated the resulting SR-enhanced samples into the computational pipeline of an iris recognition system based on a well-known public software library [12]. The remainder of this section is organized as follows. First, we describe the deep learning models employed for SR. Second, we detail the iris recognition pipeline. Third, we present the experimental protocol.

3.1. Super-Resolution Models

We selected three deep learning architectures that represent distinct families of SR strategies. We chose these models because they are widely used in the literature and have demonstrated strong performance across heterogeneous image data.

- *RCAN*: This architecture has been proposed in [8] and is a deep CNN model designed for high-accuracy image restoration. Its architecture is built on a Residual in Residual (RIR) structure, enabling the training of extremely deep networks. A channel attention mechanism is utilized to adaptively rescale channel-wise features, allowing the selective emphasis of the most informative high-frequency components. To ensure high signal fidelity, the network optimization is driven by the minimization of the L1 loss function, defined as the Mean Absolute Error (MAE) between the pixels of the reconstructed image and the ground truth.
- *ESRGAN*: This architecture has been proposed in [9] and is a GAN-based model designed to produce photorealistic images rather than focusing only on objective pixel accuracy. It improves the original SRGAN architecture by introducing the Residual-in-Residual Dense Block and removing Batch Normalization layers, which helps improve performance and reduce artifacts. ESRGAN is optimized for perceptual quality. It uses a relativistic discriminator, which learns to judge if one image is "more realistic" than another, and a perceptual loss based on VGG features extracted before the activation layer.
- *Real-ESRGAN*: This architecture has been proposed in [10] and is an advancement of ESRGAN, which targets in-the-wild images with complex and unknown degradations. Its main contribution consists of its strategy for synthesizing training data. The model is trained on purely synthetic data, but it uses a high-order degradation model. This process simulates real-world artifacts by repeatedly applying a classical degradation model (blur, resize, noise, and JPEG compression). This training allows the network to learn to remove complex, unknown artifacts rather than just reversing a simple downsampling.

The selected models were originally trained on images with characteristics different from those of iris samples. Therefore, we evaluated different training strategies using high-resolution ocular images acquired under visible-light conditions.

3.2. Iris Recognition Framework

We integrated the trained SR methods into the computational pipeline of a state-of-the-art biometric recognition system.

Depending on the dataset, we adopted different segmentation strategies. When available, we used the segmentation masks and the parameters approximating the inner and outer iris boundaries as circles provided with the datasets. Otherwise, we computed the segmentation masks using RCGAN [29] and estimated the parameters of the circles approximating the iris boundaries using the University of Salzburg Iris Toolkit (USIT) [12]. We selected RCGAN due to its high accuracy on visible-light ocular images affected by strong non-idealities [3].

For feature extraction and matching, we relied on algorithms widely adopted in the literature for images acquired with traditional iris scanners. Specifically, we used the implementations provided in USIT [12]. The feature extraction algorithm employs logarithmic Gabor filters, and the matching algorithm relies on the Hamming distance metric [30]. We selected these approaches because they are commonly used as baseline methods in iris recognition studies.

3.3. Experimental Protocol

The training protocol utilizes a dataset of 6270 high-quality ocular images acquired in natural light conditions with a resolution of 640×480 pixels. We divided the dataset into a training set containing 70% of the subjects and a test set containing the remaining 30%. SR methods are trained to reconstruct high-resolution images from low-resolution images. We obtained the high-resolution images used as targets for the training process by cropping 256×256 patches centered at the barycenter of the region of interest derived from the iris segmentation process. We generated the low-resolution images by downsampling the high-resolution images by factors of $1/2$ and $1/4$. Once the SR methods are trained, they can process images of arbitrary resolution. Therefore, the cropping step is not applied when the trained SR models are integrated into the biometric recognition pipeline.

We optimized the models using three distinct training strategies.

- *Pre-trained weights*: We used publicly available weights obtained by training the networks on diverse image datasets (DIV2K [31], Flickr2K [31], and OST [32]). It should be noted that pre-trained weights are available for Real-ESRGAN (for both $1/2$ and $1/4$ scales) and for ESRGAN (for the $1/4$ scale only).
- *Transfer learning*: We fine-tuned the pre-trained models using our iris training patches.
- *Training from scratch*: We trained the deep neural networks starting from randomly initialized weights.

To quantitatively assess the performance of the proposed framework, we employed two categories of metrics.

- *Image Quality Metrics*: We measure the quality of the high-resolution images computed by the SR methods by comparing the obtained results with the corresponding high-resolution samples used as ground truth to train the deep neural networks. Specifically, we use the figures of merit Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) [33], which assess pixel-level accuracy and structural preservation, respectively.
- *Biometric Verification Accuracy*: We evaluate the identity verification accuracy using the Equal Error Rate (EER) and Receiver operating characteristic (ROC) curves [34]. The EER represents the operating point at which the False Accept Rate (FAR) and False Reject Rate (FRR) are equal.

For each experiment, we used bilinear and bicubic interpolation algorithms as baseline techniques.

4. Experimental Results

This section presents both the quantitative and qualitative results of our experiments. We begin by analyzing image reconstruction quality using standard evaluation metrics and visual inspection on the dataset employed to train the selected SR models. Subsequently, we assess the biometric recognition performance on the same dataset. Finally, we conduct a cross-dataset evaluation using ocular images collected from websites and social media.

4.1. Datasets

To evaluate the performance of the SR methods, we used three datasets.

- *PolyU*: The training phase of our experiments utilized the Hong Kong Polytechnic University Cross-Spectral Iris Images Database [11]. Although this public database was originally created for cross-spectral research, we selected it for its high-quality images collected under visible-light conditions. This dataset is one of the largest and highest-resolution public visible-light iris databases, containing predominantly dark brown irises from Asian subjects. The database contains images from 209 subjects. For each subject, 15 instances were captured for both the left and right eyes. For this work, we used only the visible-light color images, resulting in a dataset of 6270 images (15 samples for each of the two eyes of 209 individuals). All images used in our experiments have a resolution of 640×480 pixels. We computed the segmentation masks for this dataset using RCGAN [29] and estimated the parameters of the circles approximating the iris boundaries using the USIT [12].
- *I-SOCIAL-DB*: To evaluate the generalization capability of the models in unconstrained environments, we employed the I-SOCIAL-DB [3]. This is the first public dataset of ocular images collected from portrait photographs downloaded from websites and social media. It represents a significantly more challenging scenario than traditional datasets, as the images were acquired in completely uncontrolled environments and depict uncooperative subjects. A major limitation of this dataset is that most images present an iris diameter far below 140 pixels [3], which is commonly considered the minimum diameter required by iris recognition systems [5]. Therefore, we directly use these images as input to the trained SR methods to evaluate their performance in a cross-dataset setting. The dataset consists of 3286 ocular regions extracted from 1643 face portraits of 400 individuals. For I-SOCIAL-DB, we used the provided ground-truth segmentation masks and the corresponding parameters describing the circles approximating the iris boundaries.
- *I-SOCIAL-Dark*: We created a subset of I-SOCIAL-DB, named I-SOCIAL-Dark, containing only images of dark irises. Since the PolyU dataset predominantly consists of dark eyes, while I-SOCIAL-DB includes subjects with a wider variety of eye colors, this subset allows us to analyze the performance of SR methods on challenging samples with pigmentation characteristics similar to those seen during training. The resulting subset comprises 955 images from I-SOCIAL-DB.

4.2. Image Quality Analysis

We quantitatively and qualitatively evaluated the ability of the considered SR methods to generate high-quality high-resolution images from low-resolution images obtained by downsampling the high-resolution images of the PolyU dataset. Specifically, we used the 30% portion of the PolyU dataset corresponding to the test set. Table 1 summarizes the quantitative results, showing that RCAN achieved the highest PSNR, thus producing high-resolution images most similar to the ground-truth training images. Another noteworthy outcome is that all SR models performed better when fine-tuned or trained from scratch. This result confirms that models trained on different types of images exhibit insufficient performance when applied to iris recognition systems, thereby highlighting the need for dedicated training strategies.

We also performed a visual analysis of the obtained results. Figure 2 shows examples of high-resolution images generated using different SR techniques. The figure shows that images produced by models based on deep learning exhibit a higher level of detail compared to those obtained using interpolation algorithms.

4.3. Identity Recognition Accuracy

To quantitatively evaluate the impact of SR methods on the biometric system, we analyzed the identity verification accuracy of the complete biometric pipeline [35] for samples of different resolutions. We considered the test set of the PolyU database. Table 2 summarizes the obtained EER values. The row

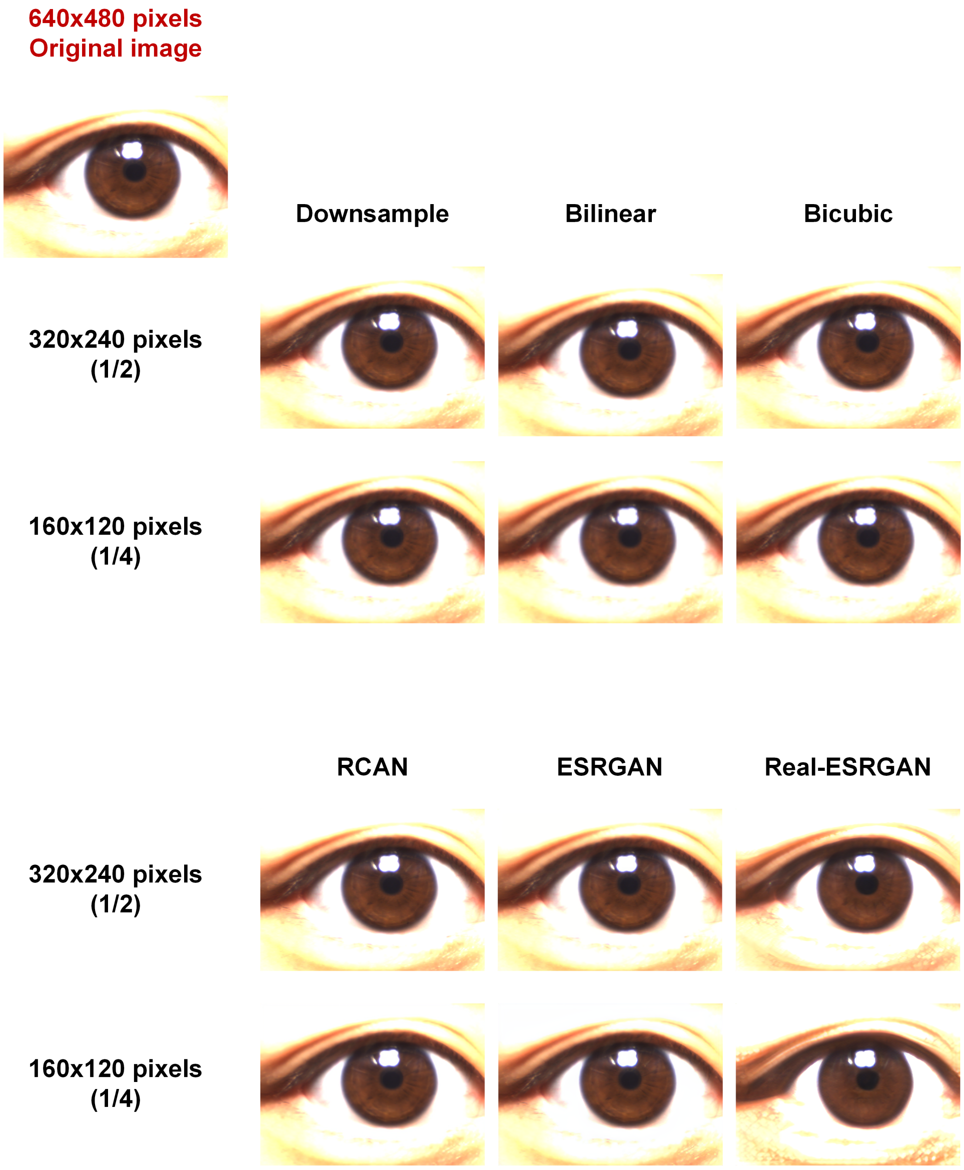

Figure 2: Comparison of different SR methods applied to a sample image of the PolyU dataset.

"Downsample" presents the baseline results obtained without applying any SR method to the low-resolution images. The table shows that ESRGAN trained from scratch achieved the best performance for the 1/2 scenario, reducing the EER from 8.32% to 7.70%. This result is not consistent with the analysis based on PSNR, as the best PSNR values were obtained using RCAN, confirming that achieving high PSNR does not necessarily translate into improved performance in biometric systems. For the 1/4 scenario, Real-ESRGAN with fine-tuning achieved the best accuracy, reducing the EER from 9.54% to 8.05%.

To provide a clearer picture of the performance improvements introduced by SR methods, Figure 3 shows the ROC curves obtained by ESRGAN trained from scratch, compared with the baseline (without any SR method) for the 1/2 scenario of the PolyU database.

Since the best results for the 1/2 scenario were obtained when training the SR models from scratch, in the following experiments we will refer only to this training strategy.

Method	Training	PSNR 320×240 Pixels (1/2)	PSNR 160×120 Pixels (1/4)	SSIM 320×240 Pixels (1/2)	SSIM 160×120 Pixels (1/4)
Bilinear	-	41.56	33.93	0.99	0.95
Bicubic	-	41.74	33.67	0.99	0.94
RCAN	Trained from scratch	49.12	41.97	0.99	0.98
ESRGAN	Pre-trained weights	N.A.	28.81	N.A	0.79
ESRGAN	Fine-tuning	N.A.	36.77	N.A.	0.96
ESRGAN	Trained from scratch	39.94	34.39	0.98	0.94
Real-ESRGAN	Pre-trained weights	38.23	31.86	0.97	0.92
Real-ESRGAN	Fine-tuning	36.91	39.13	0.96	0.97
Real-ESRGAN	Trained from scratch	36.26	31.03	0.95	0.90

Table 1
Quality of images computed using different SR approaches for the test set of the PolyU dataset. Value "N.A." indicates "Not Available" and is used in cases where the pre-trained weights of the neural network are not publicly available.

Method	Training	320×240 Pixels (1/2)	160×120 Pixels (1/4)
Downsample	-	8.32	9.54
Bilinear	-	8.16	9.11
Bicubic	-	8.12	8.68
RCAN	Trained from scratch	7.98	8.72
ESRGAN	Pre-trained weights	N.A	9.95
ESRGAN	Fine-tuned	N.A	8.47
ESRGAN	Trained from scratch	7.70	8.70
Real-ESRGAN	Pre-trained weights	8.80	10.35
Real-ESRGAN	Fine-tuned	9.22	8.05
Real-ESRGAN	Trained from scratch	9.94	12.01

Table 2
Identity verification accuracy on the test set of PolyU database, expressed in terms of EER (%). Value "N.A." indicates "Not Available" and is used in cases where the pre-trained weights of the neural network are not publicly available.

4.4. Cross-Dataset Evaluation

We performed a cross-dataset evaluation by applying the models trained from scratch on the PolyU dataset to the I-SOCIAL-DB images, without any further adaptation. The goal is to increase the iris diameter of images collected from websites and social media, thereby improving the overall robustness and accuracy of the biometric recognition process. Since high-resolution images are not available for this application context, we evaluated only the effect of SR on identity verification accuracy. The baseline EER obtained without applying any SR to I-SOCIAL-DB is equal to 17.75%. Table 3 summarizes the EER values obtained by the considered SR techniques, showing that the best result was achieved by doubling the resolution of the ocular images using ESRGAN. Specifically, the resulting EER is 17.67%.

Since the accuracy improvement obtained for I-SOCIAL-DB is smaller than that obtained for the PolyU database, we further analyzed the identity verification accuracy for images representing eyes with color characteristics more similar to those of the PolyU dataset (used to train the SR techniques). We therefore evaluated performance on the subset I-SOCIAL-Dark. The baseline EER obtained without applying any SR to I-SOCIAL-Dark is 24.40%. Table 4 summarizes the EER values obtained by the considered SR techniques, showing that ESRGAN provided the greatest contribution to biometric recognition accuracy. Specifically, doubling the original image resolution resulted in an EER of 23.90%.

The obtained results suggest that SR can effectively improve the robustness and accuracy of iris

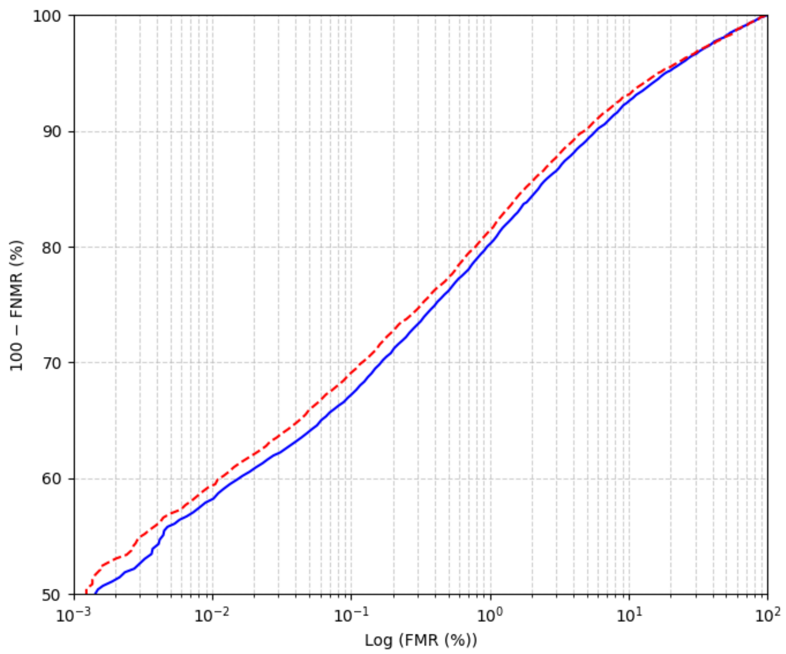

Figure 3: ROC curves illustrating the identity verification accuracy on the test set of the PolyU dataset for the 1/2 scenario, comparing ESRGAN trained from scratch with the baseline (without applying any SR method). The blue solid line represents ESRGAN, while the red dashed line represents the baseline.

recognition systems based on ocular images collected from websites and social media. However, their contribution could likely be enhanced by using training data that better reflects the non-idealities affecting web-sourced ocular images.

5. Conclusions

This paper presented a study on super-resolution techniques aimed at improving the accuracy of iris recognition for images collected from websites and social media. Specifically, we trained different deep neural networks on high-quality iris samples acquired in visible light and then applied the trained models to ocular images obtained from web sources.

To train the considered super-resolution techniques, we used the visible-light subset of the Hong Kong Polytechnic University Cross-Spectral Iris Image Database. After training the models using different strategies, we quantitatively and qualitatively evaluated the quality of the generated high-resolution images. We also analyzed the impact of super-resolution on the identity verification accuracy of a state-of-the-art iris recognition system, observing a reduction in the Equal Error Rate from 8.32% to 7.70% when doubling the image resolution using an ESRGAN model trained from scratch. We then applied the trained models to the I-SOCIAL-DB dataset, also observing improvements in recognition accuracy, especially for images depicting dark-colored eyes. In this case, doubling the image resolution using an ESRGAN model trained from scratch reduced the Equal Error Rate from 24.40% to 23.90%.

Overall, the obtained results suggest that super-resolution can effectively improve the robustness and accuracy of iris recognition systems based on ocular images collected from websites and social media. However, the contribution of super-resolution could likely be enhanced by using training data that better reflects the non-idealities present in web-sourced ocular images.

Super-resolution techniques used in conjunction with recent iris recognition technologies may increase privacy and security risks, as face images released online could be exploited to perform unauthorized biometric recognition. Investigating these aspects, including potential adversarial attacks and data misuse, represents an important direction for future research.

Method	700×600 Pixels (×2)	1400×1200 Pixels (×4)
Bilinear	17.95	17.88
Bicubic	17.72	17.68
Real-ESRGAN	22.50	21.06
ESRGAN	17.67	17.74
RCAN	17.80	17.90

Table 3
Identity verification accuracy on I-SOCIAL-DB, expressed in terms of EER (%). The baseline EER obtained without applying any SR to I-SOCIAL-DB is equal to 17.75%.

Method	700×600 Pixels (×2)	1400×1200 Pixels (×4)
Bilinear	24.35	24.13
Bicubic	24.52	24.12
Real-ESRGAN	28.79	27.68
ESRGAN	23.90	23.96
RCAN	24.50	24.52

Table 4
Identity verification accuracy on I-SOCIAL-Dark, expressed in terms of EER (%). The baseline EER obtained without applying any SR to I-SOCIAL-Dark is equal to 24.40%.

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Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT-5.2 to: Grammar and spelling check. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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