Deep Learning-based Iris Quality Assessment for Images Sourced from Websites and Social Media

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***Abstract*—Recent studies have demonstrated the feasibility of performing iris recognition by using ocular images collected from websites and social media. Unfortunately, these images often exhibit significant non-idealities due to the challenging conditions under which they are captured. Dedicated quality assessment methods could improve the accuracy and robustness of current biometric recognition technologies by identifying and discarding insufficient quality samples. However, no existing quality assessment method specifically addresses the challenges posed by samples collected in this application context. In this paper, we propose a quality assessment method based on deep neural networks, designed to address the non-idealities commonly found in ocular images collected from websites and social media. We explore three configurations of the method that leverage information from the iris localization and segmentation stages of a biometric system: (i) direct quality assessment of raw ocular images, (ii) quality assessment using iris localization data, and (iii) quality assessment incorporating both localization and segmentation data. We validated the proposed method using datasets of ocular images acquired in unconstrained conditions. The experimental results demonstrate that it significantly improves the recognition accuracy of state-of-the-art biometric systems, reducing the Equal Error Rate from 18.5% to 11.8% for I-SOCIAL-DB. Furthermore, a cross-database evaluation proves the robustness of our approach under heterogeneous and non-ideal acquisition conditions.**

***Index Terms*—Biometric, Iris, Quality, Deep learning**

I. Introduction

Iris is one of the most widely used biometric traits due to its high discriminability and temporal stability. While iris recognition has traditionally been performed in controlled settings using dedicated acquisition devices, recent studies have demonstrated the feasibility of conducting iris recognition in challenging conditions, including uncontrolled and unconstrained environments. Under such conditions, the acquired ocular images often exhibit varying illumination, occlusions, motion blur, reflections, and off-angle gaze.

With the increasing volume of high-resolution images shared on social media and other online platforms, researchers have shown the feasibility of using ocular images collected from websites and social media for iris recognition [1]. However, processing iris samples obtained in these conditions introduces new challenges due to additional non-idealities, such as those introduced by photo editing and image compression [2].

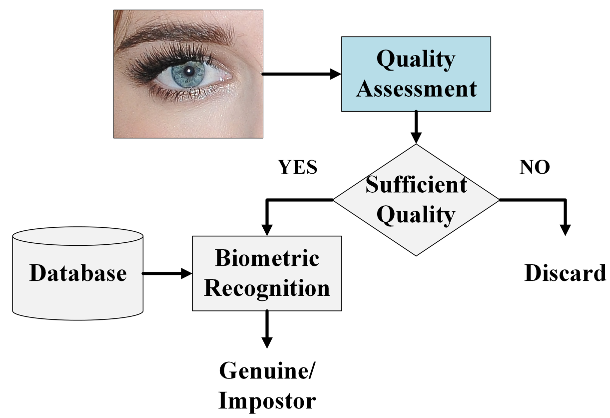


Fig. 1. Schema of an iris recognition system with quality assessment.

Previous studies have shown that poor-quality ocular images can significantly degrade the biometric recognition accuracy [3]. Automatic algorithms capable of assessing the image quality and discarding insufficient quality samples prior to biometric processing can enhance both the robustness and accuracy of biometric systems. Fig. 1 illustrates the architecture of a biometric recognition system that incorporates a quality assessment module for filtering out low-quality samples.

To analyze the ocular image quality, various methods have been proposed in the literature. These include techniques for assessing individual quality attributes [4], [5] (e.g., contrast, sharpness, and the usable area of the iris region), as well as methods that estimate the overall quality of an image [6]. While most studies focus on samples captured using dedicated iris scanners under near-infrared illumination [3], some recent efforts consider images acquired under visible light in less-constrained environments [7]. However, no existing methods are specifically designed to handle the unique non-idealities present in ocular images collected from websites and social media. Moreover, to the best of our knowledge, no prior work has investigated the role of information from the iris localization and segmentation stages of the biometric recognition pipeline in assessing image quality.

In this paper, we propose a classifier based on deep neural networks to assess the quality of iris images sourced from websites and social media. Our method is specifically designed to address the complexities and variations typical of online-collected ocular images, ensuring robust quality estimation in unconstrained environments. We introduce three configurations of our method: (i) direct application to ocular images, (ii) incorporation of information from the iris localization stage, and (iii) incorporation of information from both iris localization and segmentation stages. In addition, our method is designed for portability on edge devices, using deep neural networks with low computational complexity.

The main contributions of this work are three-fold:

- This is the first study addressing iris quality assessment using web-acquired images.
- To the best of our knowledge, this is the first study on the use of iris localization and segmentation information to improve the accuracy of quality assessment.
- We design a lightweight method suitable for deployment in edge devices by leveraging deep neural networks with limited computational requirements.

To validate our method, we evaluated both the classification accuracy of the quality assessment model and its impact when integrated into a state-of-the-art biometric recognition system. The results are encouraging: for example, our method reduced the Equal Error Rate (EER) [8] on I-SOCIAL-DB [1] from 18.5% to 11.8%. Furthermore, we conducted a cross-dataset evaluation, demonstrating the robustness of the proposed method under heterogeneous acquisition conditions.

The remainder of this paper is organized as follows. Section 2 briefly reviews related work on the assessment of iris quality. Section 3 describes the proposed method. Section 4 describes the experimental results, while Section 5 concludes the work.

II. Related Work

Quality assessment methods for iris samples can estimate either individual quality parameters related to specific sources of degradation or compute a global quality score. Many methods in the former category assess factors such as defocus blur, motion blur, off-angle distortion, occlusion, specular reflections, lighting variation, and pixel count. These parameters are often fused to produce a unified quality score. For example, [9] uses Dempster-Shafer theory to combine metrics like defocus, motion blur, and occlusion. Similarly, [10] employs a likelihood ratio-based fusion strategy, while [11] uses Principal Component Analysis to merge factors including mean intensity, entropy, blur, and occlusion. The method in [7] personalizes the quality evaluation based on individual iris structure variation, whereas [12] introduces a dynamic weight-based fusion mechanism to integrate iris and face quality scores for enhanced recognition. The study in [13] computes statistical features such as average gray level, contrast, smoothness, and entropy, classifying iris images into quality categories using ensemble classifiers. Additionally, the work presented in [14] refines Daugman's method [15] by modifying it to isolate high-frequency components for quality estimation. The method proposed in [16] applies a possibilistic reasoning approach, using contextual indicators like occlusion, contrast, and homogeneity for multi-level quality classification. The study presented in [17] proposes a medoids-based clustering technique to estimate segmentation quality and prevent errors in biometric recognition.

Most iris quality assessment studies have focused on images captured under near-infrared light. However, some methods have been proposed for visible-light images, which present additional challenges due to uncontrolled lighting and pigmentation variability. For instance, the method described in [7] assesses the quality based on focus, motion blur, occlusions, and pigmentation, utilizing segmentation outputs to improve the estimation and recognition performance. Similarly, the approach presented in [18] introduces the Differential Sign-Magnitude Statistics Index, a no-reference quality metric designed for real-time assessment of iris images captured by handheld devices under visible light. An enhanced version, presented in [19], incorporates additional statistical features, such as local intensity variations, to improve the segmentation accuracy and overall recognition reliability.

Recent advancements in iris quality assessment increasingly rely on deep neural networks rather than hand-crafted features. For example, [20] employs a Convolutional Neural Network (CNN) to extract features from image patches for quality estimation. In contrast, [6] utilizes attention mechanisms to estimate the distance between image features and an ideal reference. The study in [21] explores deep learning compression techniques for quality assessment and compares them with traditional methods. Furthermore, the work in [5] presents a real-time framework for iris detection and quality evaluation in video streams, using deep learning to assess image sharpness and texture diversity.

To the best of our knowledge, no existing quality assessment techniques have been specifically designed for iris images collected from websites and social media. Moreover, no prior studies have analyzed the potential benefit of incorporating information from the iris localization and segmentation stages of the biometric recognition process into the quality assessment task.

III. Proposed Method

We present a novel automated method for assessing the quality of iris samples collected from websites and social media. The goal is to categorize ocular images by quality, ensuring that only sufficient-quality samples are used in the recognition process. The method employs a binary classifier based on deep neural networks. The quality assessment method operates in three configurations, depending on the input: Configuration A analyzes the full ocular image; Configuration B focuses on the iris region obtained after localization; and Configuration C applies a mask to the foreground regions of the ocular image. Fig. 2 illustrates the overall structure of the proposed method in the described configurations.

A. Deep neural networks

In this work, we consider different deep neural networks for iris quality assessment. Every neural model was pretrained

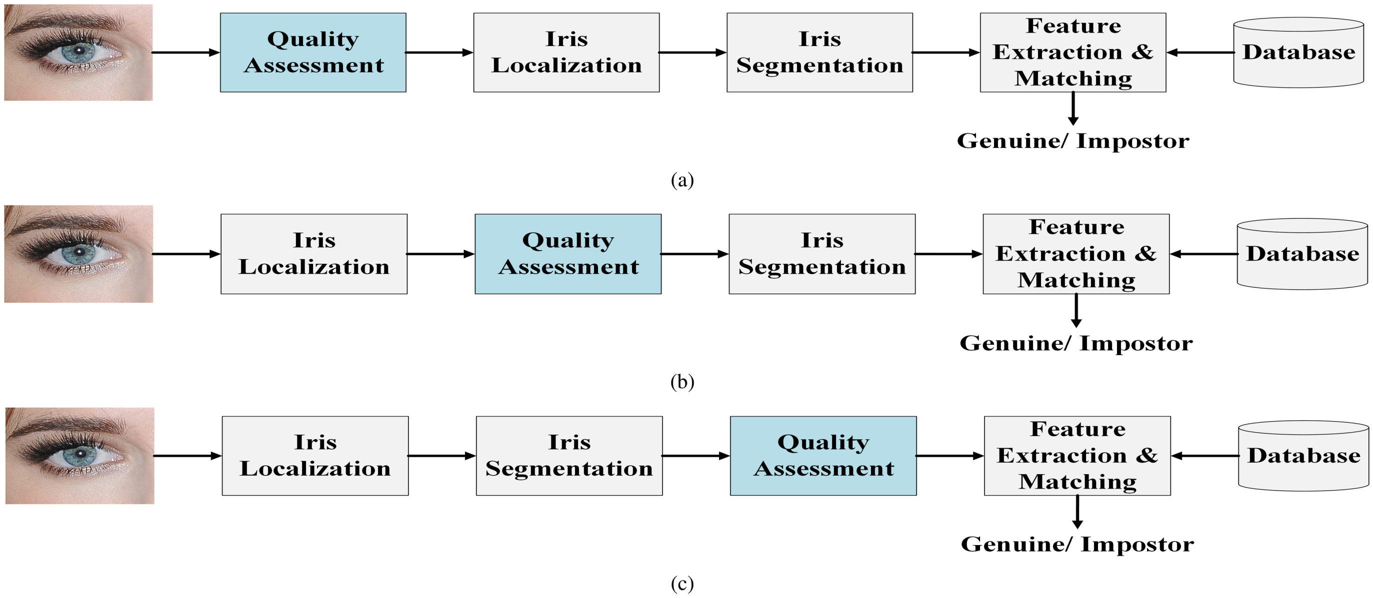


Fig. 2. Configurations of the proposed quality assessment method: (a) Configuration A takes an ocular image as input; (b) Configuration B exploits information computed during the iris localization step; (c) Configuration C uses information obtained by the iris localization and segmentation steps.

on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) dataset [22], consisting of $1,281,167$ training images, before being fine-tuned for our iris quality assessment task.

The selected deep neural networks include models designed for both general-purpose computational platforms and edge devices, ensuring a balance between accuracy and efficiency. For general-purpose architectures, we consider AlexNet [23], a pioneering CNN with five convolutional layers followed by three fully connected layers; VGG-16 [24], a 16-layer deep CNN known for its uniform structure and strong feature extraction capabilities; and multiple versions of ResNet [25], including ResNet-18 and ResNet-34, which utilize residual learning to mitigate the vanishing gradient problem.

For deployment on edge devices, we include SqueezeNet [26], which achieves high accuracy with significantly fewer parameters by employing Fire modules; EfficientNet-B0 [27] optimizes accuracy and computational efficiency through a compound scaling method, making it suitable for various image recognition tasks; MobileNet-V3 [28], designed for mobile and resource-constrained applications, which uses depthwise separable convolutions and efficient network pruning; and Inception-V1 (GoogLeNet) [29], which leverages inception modules to enable multi-scale feature extraction while maintaining computational efficiency.

Each of these networks was fine-tuned for our dataset, leveraging manually labeled quality scores as ground truth.

B. Confiugurations of the proposed method

To evaluate the impact of different input representations on the quality classification, we propose three configurations of our method.

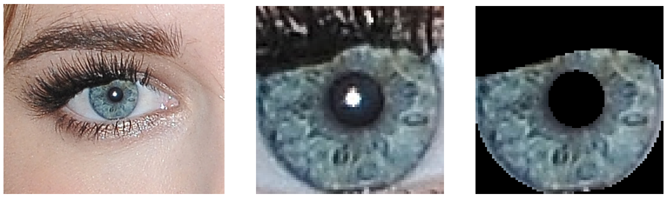
i) *Configuration A:* This configuration takes an ocular image as input. No additional information is provided to the neural classifier.
ii) *Configuration B:* The classifier uses an image cropped from the original ocular sample by considering a squared region representing the bounding box of the circle approximating the iris boundary estimated during the iris localization step of the biometric recognition process. By isolating the iris region, this approach ensures that the quality classification is driven only by iris-related features.
iii) *Configuration C:* The classifier uses an image obtained by multiplying the cropped ocular image of Configuration B with the corresponding segmentation mask. Using the binary mask, we set the non-iris regions to black, while preserving the iris area. This approach ensures that only the iris texture contributes to quality classification, while occlusions, eyelashes, and surrounding areas are suppressed.

Fig. 3 shows an example of input ocular image for each configuration of the proposed method.

IV. Experimental Results

We conducted a series of experiments to evaluate the accuracy of the proposed quality assessment method, its impact on the performance of a state-of-the-art iris recognition system across different datasets, and the possible causes of classification errors.

This section describes the datasets used, testing protocols, classification experiments, integration of the quality assessment method into a state-of-the-art iris recognition system, cross-database performance evaluation, and a qualitative analysis of the results.



(a) (b) (c)

Fig. 3. Example of input ocular image for every configuration of our quality assessment method: (a) Configuration A, (b) Configuration B, (c) Configuration C.

TABLE I
CLASSIFICATION ACCURACY OF DIFFERENT DEEP NEURAL NETWORKS

Architectures	Acc. (%)	FP (%)	FN (%)
AlexNet	77.79	13.18	9.03
VGG-16	79.92	11.05	9.03
ResNet-18	71.81	9.74	18.46
ResNet-34	75.36	15.21	9.43
EfficientNet-B0	77.89	11.46	10.65
SqueezeNet	76.57	9.74	13.69
MobileNet-v3	76.47	10.85	12.68
Inception-v1	79.51	13.08	7.40

A. Datasets

To evaluate the performance of the quality assessment method, we use the following two datasets:

- *I-SOCIAL-DB* [9] is a publicly available dataset composed of images collected from websites and social media. It contains $3,286$ ocular images extracted from $1,643$ high-resolution facial portraits of 400 individuals. Each ocular image is paired with a manually annotated segmentation mask that provides pixel-wise labels for the iris, occlusions, and reflections. For each image, the dataset includes parameters describing the circles approximating the inner and outer iris boundaries, estimated by a human expert.
- *NICE.I* is the training set used in the NICE.I competition [30], and it consists of a subset of UBIRIS v2 [31]. The dataset includes 452 ocular images acquired in natural light conditions with subjects in motion, belonging to 204 eyes. Each image is accompanied by a manually annotated segmentation mask. Since the dataset does not provide the parameters for the inner and outer iris boundary circles, we estimated these parameters from the segmentation masks using the algorithm described in [32].

A human expert classified each ocular image into sufficient quality (1) and insufficient quality (0).

We trained the quality assessment method using I-SOCIAL-DB, and evaluated its robustness under heterogeneous application conditions using NICE.I through cross-dataset validation.

B. Biometric recognition system

To evaluate the impact of our quality assessment method on identity verification applications, we integrated it into a state-of-the-art iris recognition system. Specifically, samples classified as having insufficient quality were discarded, while those deemed of sufficient quality were processed by the biometric system.

In this study, we use the iris segmentation masks provided by the considered datasets, along with the circles approximating the iris boundaries described in Section IV-A. For feature extraction and matching, we employed the University of Salzburg Iris Toolkit (USIT) [33] for feature extraction and matching. Specifically, the feature extraction process employs Logarithmic Gabor (LOG) filters [34], and the matcher is based on the Hamming Distance (HD) metric [35]. We selected these feature extraction and matching algorithms since they are used as reference methods in a wide number of studies.

C. Testing protocol and figures of merit

To evaluate the classification accuracy of the proposed quality assessment method, we used the following figures of merit: Accuracy, False Positive Rate (FPR), and False Negative Rate (FNR) [36].

To evaluate the effect of the proposed method on the performance of a biometric recognition system, we analyzed the identity verification accuracy by considering the EER and Receiver Operating Curve (ROC) [8].

D. Classification accuracy

For training and evaluating the proposed quality assessment method, we split I-SOCIAL-DB into 70% of the subjects for training and 30% for testing, ensuring a subject-wise division to prevent data leakage. Given that I-SOCIAL-DB consists of 400 subjects, this split results in 280 subjects for training and 120 subjects for testing, corresponding to $2,300$ training images and 986 testing images. Since every subject has between 2 to 6 images per eye, this distribution provides a balanced representation of the quality variations across the dataset.

To match the input layer dimensions of the considered deep neural networks, the images have been resized to 224×224 pixels before training. Given the inherent class imbalance, where the majority of images belong to the sufficient quality class (1), we applied data augmentation techniques to enhance the model's robustness. Augmentation methods include rotations, flipping, contrast adjustments, and Gaussian noise addition. Additionally, class-balancing techniques have been employed to prevent bias toward the majority class, ensuring fair classification of both sufficient- and insufficient-quality images. The models have been trained using a batch size of 32, ADAM optimizer, and a learning rate of 0.00001.

To determine the most effective deep learning model for iris quality classification, we compared several neural architectures for every configuration. Table I resumes the results achieved by different deep neural networks for Configuration A.

Table I shows that VGG-16 obtained the best performance, with a classification accuracy of 79.92%. Therefore, we employed VGG-16 for the following tests. Anyway, models designed for being ported into edge devices obtained similar

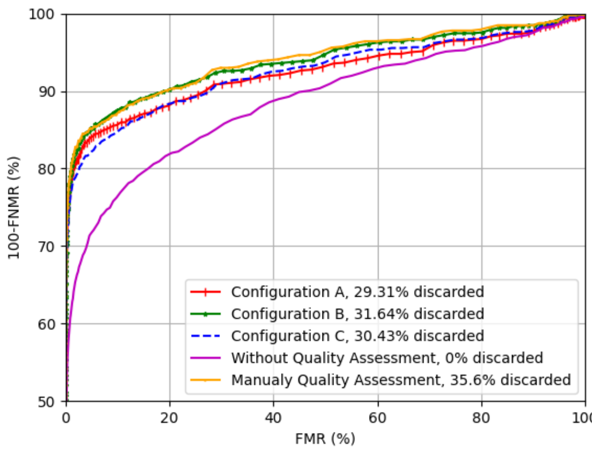


Fig. 4. Identity verification accuracy obtained using a well-known iris recognition system [34] and the different configurations of the proposed quality assessment method for I-SOCIAL-DB. Each configuration of our method improves the accuracy of the biometric system.

TABLE II
EER AND DISCARDED SAMPLES FOR I-SOCIAL-DB

Method	EER (%)	Discarded Samples (%)
Without quality assessment	18.5	0
Manual quality assessment	11.8	35.60
Configuration A	13.6	29.31
Configuration B	11.8	31.64
Configuration C	13.3	30.43

performance. As an example, Inception-v 1 obtained a classification accuracy of 79.51%.

E. Impact on the performance of the biometric system

To analyze the impact of our quality assessment method on biometric recognition, we compared the three configurations of our method with that obtained without applying any quality assessment, and the quality estimation performed by a human operator during the image labeling. We considered only the subset of testing images of I-SOCIAL-DB. Fig. 4 shows the obtained ROC curves, while Table II summarizes the obtained results.

Fig. 4 and Table II show that our quality assessment method can effectively discard low-quality samples, thus increasing the identity verification accuracy of the biometric system.

The initial biometric system, operating without quality assessment, achieved EER of 18.5%. For the less computationally expensive configuration, Configuration A, the EER improved to 13.6%. Among the three proposed configurations, Configuration B was the most effective, leveraging iris localization to refine quality assessment. Configuration C, which additionally incorporated binary mask segmentation, resulted in a slightly higher EER of 13.3%, indicating that segmentation didn't offer much additional value beyond what localization already provided. Furthermore, as shown in Table II, Configuration B has a EER that is similar to that of manual or human expert labeling.

F. Comparison with algorithmic techniques

Algorithmic approaches for assessing the quality of iris samples typically estimate a score that quantifies a single type of non-ideality in the images. Since one of the most significant issues in ocular images collected from websites and social media is poor focus of the iris pattern, we compared our method with a widely adopted algorithm for evaluating the focus quality of iris samples [15]. Specifically, this algorithm computes a focus score by summing the normalized response to a Gaussian-based filter. A higher score indicates better focus quality. We used the obtained focus scores to classify ocular images as having either sufficient or insufficient quality. In particular, we assigned class 0 (insufficient quality) to a number of samples equal to the number labeled as class 0 by a human expert (35.6% of the ocular images), and class 1 to the remaining samples.

We then evaluated the impact of this algorithmic approach on the biometric recognition system. For a fair comparison with our method, we used the test set of I-SOCIAL-DB, excluding the samples classified as class 0 from the dataset. The obtained EER is equal to 16.53%. This result demonstrates that, although the algorithm enhances the performance of the original biometric recognition system, its contribution to the final recognition accuracy is smaller than that provided by our quality assessment method. This is because deep neural networks are capable of learning and identifying a broader range of non-idealities in the samples compared to an algorithmic approach that evaluates only a single non-ideality.

G. Cross-dataset evaluation

To analyze the robustness of our quality assessment method across different populations and acquisition conditions, we conducted a cross-dataset evaluation. For this test, we applied the best-performing architecture on I-SOCIAL-DB (VGG-16) to the samples of NICE.I, without performing any additional training or fine-tuning. Images classified as having insufficient quality were excluded from the biometric recognition process. The results are summarized in Table III.

Table III shows that every configuration of the proposed quality assessment method reduced the EER compared to the baseline where no quality assessment was applied. In particular, Configuration B reduced the EER from 35.14% to 24.47%. Notably, the EER obtained for I-SOCIAL-DB is lower than that for NICE.I. This is expected, as the NICE.I dataset contains ocular images with significant occlusions, having been designed to evaluate the performance of segmentation algorithms under challenging conditions. Nonetheless, the results confirm the generalization capability of the proposed method, which effectively identified insufficient-quality samples in a dataset characterized by acquisition conditions different from those of the training data.

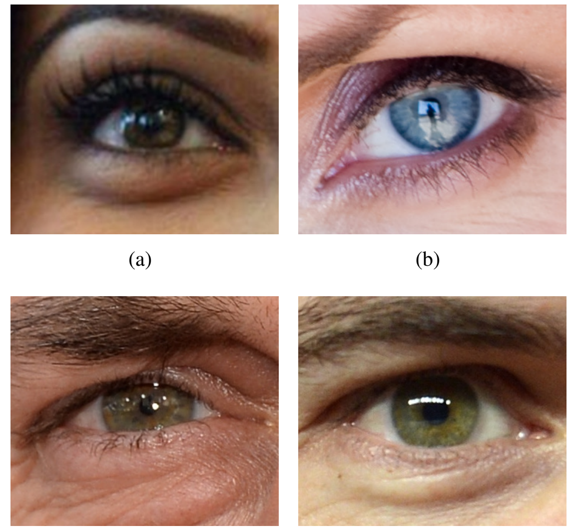
H. Qualitative analysis

We conducted a visual analysis of the classification results produced by our quality assessment method, observing that

TABLE III
EER AND DISCARDED SAMPLES FOR A CROSS-DATASET EVALUATION (CLASSIFIER TRAINED ON I-SOCIAL-DB AND TESTED ON NICE.I)

Method	EER (%)	Discarded Samples (%)
Without quality assessment	35.14	0
Manual quality assessment	28.91	53.89
Configuration A	25.17	54.42
Configuration B	24.47	46.68
Configuration C	25.26	85.62

the majority of classification errors occurred when insufficient-quality samples were misclassified as sufficient. Most errors were caused by unusual specular reflections, likely due to the limited number of similar samples in training. As an example, Fig. 5 shows four classification results obtained for ocular images affected by reflections. Fig. 5 (a) and Fig. 5 (b) are insufficient quality samples correctly classified as such; Fig. 5 (c) and Fig. 5 (d) are insufficient quality samples incorrectly classified as sufficient quality due to the presence of reflections with unusual shapes.



(a) (b) (c) (d)

Fig. 5. Examples of ocular images affected by reflections: (a) and (b) are insufficient quality samples correctly classified as such; (c) and (d) are insufficient quality samples incorrectly classified as sufficient quality due to the presence of reflections with unusual shapes. Most classification errors occurred in the presence of specular reflections with uncommon shapes.

V. CONCLUSIONS

This paper presented the first study on quality assessment of iris samples collected from websites and social media. We proposed a method based on deep neural networks to detect and discard ocular images of insufficient quality. Furthermore, we proposed three configurations of the quality estimation method to exploit in different ways information obtained from the iris localization and segmentation steps.

We trained our method on I-SOCIAL-DB, achieving the best classification accuracy using VGG-16. Among the three configurations, the one that uses only the ocular image as input (Configuration A) achieved strong performance by reducing the Equal Error Rate (EER) from 18.5% to 13.6%. Configuration B achieved the highest overall accuracy, with an EER of 11.8%, but requires additional computation compared to Configuration A, as it depends on information obtained from iris localization algorithms, which are often based on deep neural networks. Furthermore, we performed a cross-dateset evaluation by applying the best performing network trained for I-SOCIAL-DB to a subset of samples of UBIRIS v2, proving the robustness of the proposed method to heterogeneous acquisition conditions. A visual analysis of the classification results suggested that most of the classification errors of our quality assessment method are caused by the presence of specular reflections with uncommon shapes.

Future work should focus on analyzing the performance of the proposed approach across additional populations, acquisition conditions, and biometric recognition systems. In particular, the quality assessment method should be validated in real-world application scenarios. A promising direction for future research would be to evaluate the quality of both iris and face biometric traits from portraits collected from websites and social media. Finally, efforts should be made to effectively deploy the quality assessment method on edge devices, optimizing the computational time and energy consumption.

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