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Unified Face Image Quality Score based on ISO/IEC Quality Components

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Abstract: Face image quality assessment is crucial in the face enrolment process to obtain high-quality face images in the reference database. Neglecting quality control will adversely impact the accuracy and efficiency of face recognition systems, resulting in an image captured with poor perceptual quality. In this work, we present a holistic combination of 21 component quality measures proposed in "ISO/IEC CD 29794-5" and identify the varying nature of different measures across different datasets. The variance is seen across both capture-related and subject-related measures, which can be tedious for validating each component metric by a human observer when judging the quality of the enrolment image. Motivated by this observation, we propose an efficient method of combining quality components into one unified score using a simple supervised learning approach. The proposed approach for predicting face recognition performance based on the obtained unified face image quality assessment (FIQA) score was comprehensively evaluated using three datasets representing diverse quality factors. We extensively evaluate the proposed approach using the Error-vs-Discard Characteristic (EDC) and show its applicability using five different FRS. The evaluation indicates promising results of the proposed approach combining multiple component scores into a unified score for broader application in face image enrolment in FRS.

Keywords: Biometrics, ISO/IEC face quality components, Face recognition system, Face image quality assessment.

1 Introduction

Owing to their convenience, unobtrusiveness, and enhanced performance, Face Recognition Systems (FRS) have become widely adopted in recent years for applications such as forensic investigations and border controls. As these systems have become a cornerstone element in our security infrastructure, their reliability is very important. The performance of facial recognition systems depends on the quality of the images presented to them. Reference face images of higher quality are expected to support better recognition performance, and poor-quality images can degrade the performance of these systems on all tasks. Assessing quality itself remains a challenge [Me22, CAN23]. Several studies in the existing literature have considered dealing with low-quality images and developing robust FRS to account for low quality [CY23]. While this is a positive aspect of technology advancement, enrolment systems need high-quality images for different use cases. For instance, a high-quality face image is needed in the passport application process, which a human expert (e.g., passport issuing officer) can also use to verify the identity and confirm the pre-set quality standards. Furthermore, a low-quality face image can lead to incorrect decisions

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owing to perceptible face regions (occlusion or bad illumination) [Sc22, CSN20]. ISO/IEC

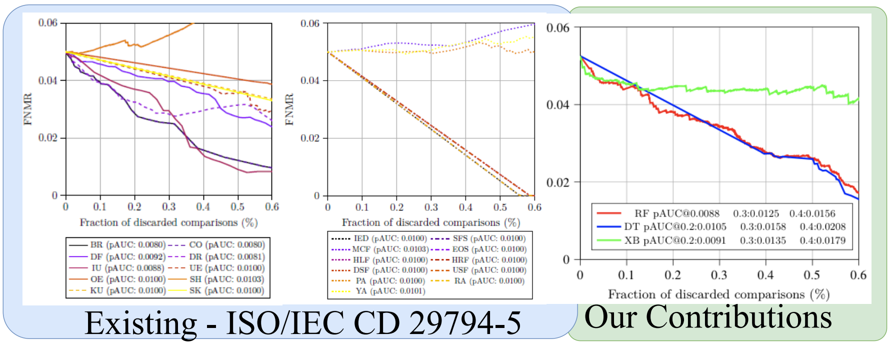


Fig. 1: Contributions of this work in unifyed the ISO/IEC CD 29794-5 quality components

29794-5:2023 [IS23] is intended to standardise face image quality measures and therefore categorizes factor-specific measures as subject-related or capture-related. ISO/IEC 29794-5:2023 [IS23] proposes independent quality components to assess different aspects of a face image such as Brightness (BR), Constrast (CO), Defocus (DF), Dynamic Range (DR), Illumination Uniformity (IU), Under-exposure (UE), Over-exposure (OE), Sharpness (SH), Kurtosis (KU), Skewness (SK), Inter eye distance (IED), Single face subject (SFS), Mouth closed (MCF), Eyes open (EOS), Horizontal left shift face (HLF), Horizontal right shift face (HRF), Vertical down shift face (DSF), Vertical upward shift face (USF), Pitch angle (PA), Roll angle (RA), Yaw angle (YA). However, recent deep learning systems provide a holistic quality measure for face images. Thus, developing a unified quality score for ISO/IEC CD 29794-5 makes it possible for operational systems to obtain one score (e.g., similar to NFIQ for fingerprints [Ta21] or to compare it against a unified score of DL-based systems. In this work, we combined the quality components of ISO/IEC CD 29794-5 to a single quality score using well-tested machine learning techniques (MLT) such as Random Forest (RF), Decision Tree (DT), and XGBoost (XB). We demonstrated that RF, DT, and XGBoost can be used to obtain a unified score for different databases, FRS, and FIQA measures. We assert the validity of the idea by evaluating it on three different public face datasets such as Labeled Faces in the Wild (LFW) [Hu07], XQLFW [KHR21], and color FERET [Ph98] to cover different kind of use cases. The contributions of this work are summarized as follows:

- a new approach towards a unified face image quality score using ISO/IEC 29794-5 that include 10 capture-related measures and 11 subject-related measures as shown in Figure 1.
- an extensive evaluation of the proposed method for obtaining a unified score as a predictor for the FRS performance using the Error-vs-Discard Characteristic (EDC).
- the evaluation is demonstrated on three diverse datasets with various quality factors using state-of-the-art supervised and unsupervised FIQA and diverse FRS.

In the rest of the paper, we present a set of related works in Section 2. Section 3 presents a detailed method description. Section 4 presents an experimental setup and evaluation.

Section 5 presented the results. Section 6 discusses the limitations of this work. In the final Section 7, the conclusion is discussed.

2 Related Work

While there exist a number of works for estimating the quality of face images, in this section, we present the most relevant works related to our work. A recent survey of this comprehensive picture can be found in [Sc22]. A set of standards has been proposed to ensure face image quality by constraining capture requirements, such as ISO/IEC 39794-5 [IS19] and ICAO 9303 [In21]. Assessment of face images quality is typically divided into capture-related measures that are affected by external circumstances caused by the capture device (such as brightness, illumination, and motion blur) and subject-related measures (such as facial expression, pose, and occluded facial parts) [Sc22].

FIQA approaches that include supervised learning algorithms based on human or artificially constructed quality labels have become increasingly popular because of their performance [BVS13, ZZL17, KGV20, RM14, Wa17]. The utilized algorithms include cumulative distribution with an SVM-based approach [BVS13], Spearman and Kendall rank-order correlation coefficient-based learning [ZZL17], Gaussian function-based de-focus, and motion blur intensity [KGV20]. Wasnik et al.[Wa17] examined FIQA in the context of smartphone-based FR, evaluating eight FIQAs specifications and proposed a vertical edge density FIQA for lighting and pose symmetry.

However, human perception may not always correlate with the details sought by the FRS and utility values derived from comparison scores. They rely on an error-prone labeling approach and require large-scale training datasets. SER-FIQ [Te20] is an unsupervised learning-based method that measures the face recognition model-specific quality by comparing the output embeddings of several randomly chosen sub-networks without requiring any ground truth quality score training labels. Supervised learning-based MagFace approach from Meng et al.[Me21] integrates FIQA within the FRS. This approach works by extending ArcFace [De19] training loss, changing the angular margin to a magnitude-aware angular margin, and adding magnitude regularization. Another supervised learning-based CR-FIQA is a recent face image quality assessment method introduced by Boutros et al.[Bo23], which estimates the quality of a facial image by predicting its relative classifiability. The classifiability of an image is measured based on the location of the feature representation in the angular space with respect to its class center and the nearest negative-class center. However, these methods incur additional computational costs or network blocks, which complicates their use in conventional face systems. So far, research on FIQA has directly utilized the FRS model during FIQA model inference without FIQA model training on ground truth quality scores. On the other hand, hybrid FRS/FIQA approaches simultaneously train FRS and FIQA as part of a single integrated framework, generating both face recognition and quality assessment output during inference.

2.1 ISO/IEC 29794-5 and Unified FIQA Score

While holistic FIQA scores are based on DL methods, ISO/IEC 29794-5 and its reference implementation OFIQ will typically be used in operational settings for various purposes, such as enrolment into national ID databases. Further, looking into each qaulity component can be tedious, and obtaining a baseline score decreases the labor involved in rejecting an image or in understanding the component on which the captured subject has to act. Thus, there is a need to combine the component measures into a unified score, making it compatible with DL-based FIQA without explicit ground truth annotation. A possible solution is to use the quality score provided by DL systems as the ground truth to create good and bad classes corresponding to the face quality vector obtained from different component measures. Using the ground truth provided by the DL-based FIQA, a classifier can be trained to obtain a unified score from the component measures.

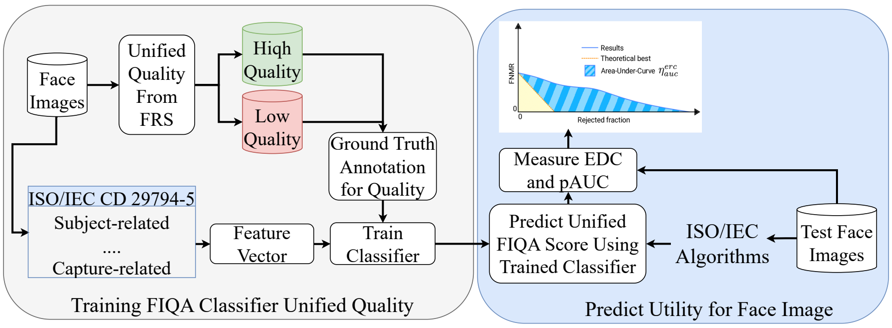


Fig. 2: Proposed approach for overall quality assessment.

3 Proposed Method

We propose an approach parallel to NFIQ2.0 to estimate the quality of face images. Fig 2 shows the steps in calculating the overall quality score for an input face image using 21 face image quality components for ISO/IEC 29794-5:2023. The first step is uncontrolled face detection using an InsightFace-based RetinaFace [De20]. In the second step, alignment, cropping, and resizing were performed using InsightFace-based ArcFace [De19]. The aligned image is further used to obtain 21 quality measures from ISO/IEC CD 29794-5, and can be represented as $F_{qc} = \{f_1, f_2 \dots f_{21}\}$ for all independent components. Each native quality measure is further normalized to a uniform range of 0 to 100 where a low value represents poor quality and a high value represents better image quality. However, the estimated component measures cannot individually indicate the quality or utility of a face image. Therefore, we used an auxiliary FRS that can estimate face quality. The obtained quality score from a DL-based system was further binned as good quality and bad quality for ground truth annotation in training a supervised classifier. For the sake of simplicity, we consider a hard threshold of normalized quality score of 70 to decide as good quality or bad quality. In particular, we used the FIQA algorithms CR-FIQA, MagFace, and SER-FIQ independently and all of them can provide a unified score. The F_{qc} consisting of 21 component measures was then estimated for the test set to establish the utility of the face image using the trained classifier. The utility was further measured using EDC and pAUC for various FRS such as FaceNet, ArcFace, PFE, MagFace, and ElasticFace.

4 Experimental setup and Performance Evaluation Metrics

We analyzed the performance of our proposed fusion method using three state-of-the-art FIQA models: CR-FIQA [Bo23] which adds regression networks to the recognition models for learning identity quality; MagFace [Me21] which associates the magnitude of face embeddings with face quality; and SER-FIQ [Te20] which employs several sub-networks of a recognition model to generate quality scores. We utilized pretrained models to extract embeddings for our analysis [Bo23, Me21, Te20]. Further, we conduct all our face-quality assessment experiments on LFW [Hu07], XQLFW [KHR21], and color FERET [Ph98] publicly available datasets that represent varying quality and diversity to study the generalization of the proposed approach.

4.1 Evaluation metrics

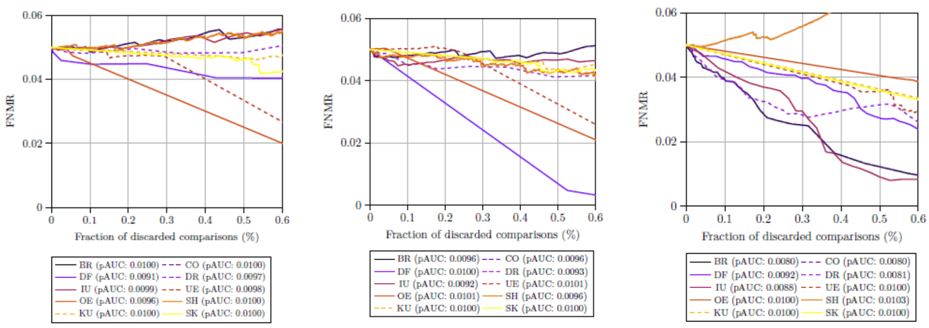
To evaluate the face quality assessment algorithm performance, we employ the "Error versus Discard Characteristic" (EDC) standardized by ISO/IEC 29794-1[3] and the consequent partial Area Under the Curve (pAUC) values are reported [Sc23]. Furthermore, the EDC curves are plotted at a fixed FMR 0.1% as recommended for border control operations by Frontex [4]. EDC curves measure the performance of a given FRS when the percentage of the lowest-quality face images is discarded. Because discarding a large portion of all images is not a practical application scenario, we are typically interested in lower discard rates. Therefore, we report the partial area under the curve (pAUC) of the EDC at a discard rate of 20% for an FNMR of 0.05 starting error [Sc23].

5 Experiments and Results

In the following section, we present the results of our experiments conducted to investigate: (i) The performance of the implemented 21 ISO/IEC 29794-5 capture and subject-related measures was evaluated using three datasets: LFW, XQLFW, and color FERET. (ii) Performance analysis between CR-FIQA, MagFace, and SR-FIQ techniques and the impact of ArcFace, FaceNet, PFE, MagFace, and ElasticFace FRS models with the proposed FIQA quality measure fusion approach on three datasets. The evaluation of FIQA algorithms depends on face verification error rates. To evaluate the generalization of the methods, we investigate how well the quality components are generalising for five different state-of-the-art FRS to report the verification performance at different discard fractions

[3] https://www.iso.org/standard/79519.html

[4] Best practice technical guidelines for automated border control (abc) systems



(a) LFW (b) XQLFW (c) color FERET

Fig. 3: EDC and pAUC score at 0.2 discard rate on different datasets result of ISO capture quality components.

to inspect the generalizability of FIQA over FRS. We choose FaceNet [SKP15] based on softmax loss, Probabilistic Face Embeddings (PFE) [SJ19] based on Gaussian distribution, ArcFace[De19]. In addition, we also analyzed MagFace [Me21] and ElasticFace [Bo22] as both are based on adaptive angular marginal loss. For each of the five FRS, the images were prepossessed, as described in the corresponding reference. The embedding was extracted from the last layer of each model, and cosine similarity was used to generate comparison scores for face verification experiments.

5.1 ISO/IEC CD 29794-5 Quality Measures

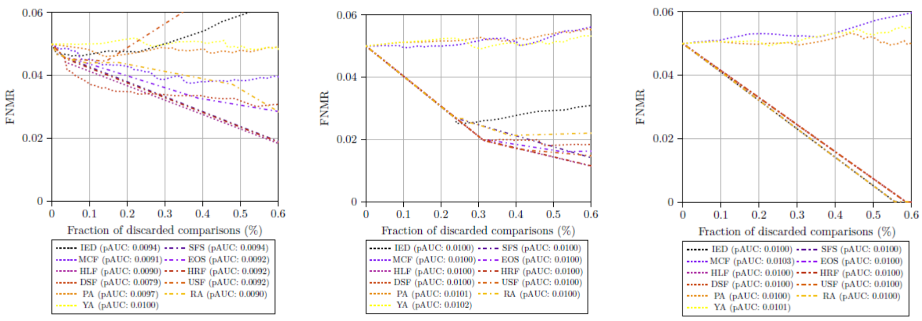
First, we report the performance of each of the 21 ISO/IEC 29794-5 quality measures, which include both capture- and subject-related measures using EDC curves and pAUC, as shown in Fig 3 (capture related) and Fig 4 (subject related) for the LFW, XQLFW, and color FERET datasets, respectively. We make the following observations by analyzing the independent component measures.

5.2 Capture related measures

- For LFW in Fig 3a Skewness (SK) and Kurtosis (KU) FNMR decreases slowly and drops around the 50% discard rate. Brightness (BR), Contrast (CO), Illumination Uniformity (IU), Dynamic Range (DR), and Sharpness (SH) demonstrate the same behavior where the error rate constantly increases, which shows that on the LFW dataset a non-correlation to utility. The error rates for Under-exposure (UE), Over-exposure (OE), and Defocus (DF) have a steady decrease showing correlation to the measure as a utility indicator.
- For XQLFW We can observe that the FNMR for DF, OE, and UE decrease steadily indicating the utility as shown in Fig 3b. The error rates of BR, IU, Kurtosis KU, and CO have the similar characteristic and remain constant regardless of the discard

rate indicating no correlation to utility from these measures for XQLFW. SK, SH and DR demonstrate the same behaviour where the error rate increases slowly and drops around the 60% discard rate.

- In Fig 3c, we can see for colorFERET that the FNMR of BR, CO, DF, DR, IU, UE, OE, KU, SK brightness and variance show the same behavior and they decrease quite steadily as the discard rate increases indicating a good correlation as a utility predictor on color FERET dataset. However, the FNMR for SH increased after 20% discard rate, indicating no correlation for utility on the color FERET dataset.



(a) LFW (b) XQLFW (c) color FERET

Fig. 4: EDC and pAUC score at 0.2 discard rate on different datasets result of ISO subject quality components.

5.3 Subject related measures

The EDC plots for subject-related measures are provided in Fig 4 for LFW, XQLFW, and color FERET dataset, respectively. We make the following observations as noted below:

- For LFW we can observe the FNMR values for Vertical Down Shift Face (DSF) and Mouth Closed (MCF) remain constant after a slight drop at the beginning indicating a weak correlation to utility. The error rate remains relatively unchanged for Inter eye distance (IED), Vertical upward shift face (USF), Yaw angle (YA), and Pitch angle (PA) before a steady increase after a discard ratio of 20% indicating no strong correlation with utility. However, the FNMR for Roll angle (RA), Single face subject (SFS), Horizontal right shift face (HRF), and Eyes open (EOS) components steadily decrease indicating a strong relationship between utility and FNMR in the case of LFW dataset.
- For the XQLFW dataset we can further observe the FNMR for MCF, YA, and DSF increase steadily as the proportion of discarded images increase indicating no strong correlation with utility for XQLFW dataset as shown in Fig 4b. However, a moderate correlation can be observed for IED upto 30% discard and no significant relation beyond. In addition, RA, DSF, USF, SFS, MCF, EOS, the error rate decreases sharply, demonstrating a strong correlation between quality components and utility.

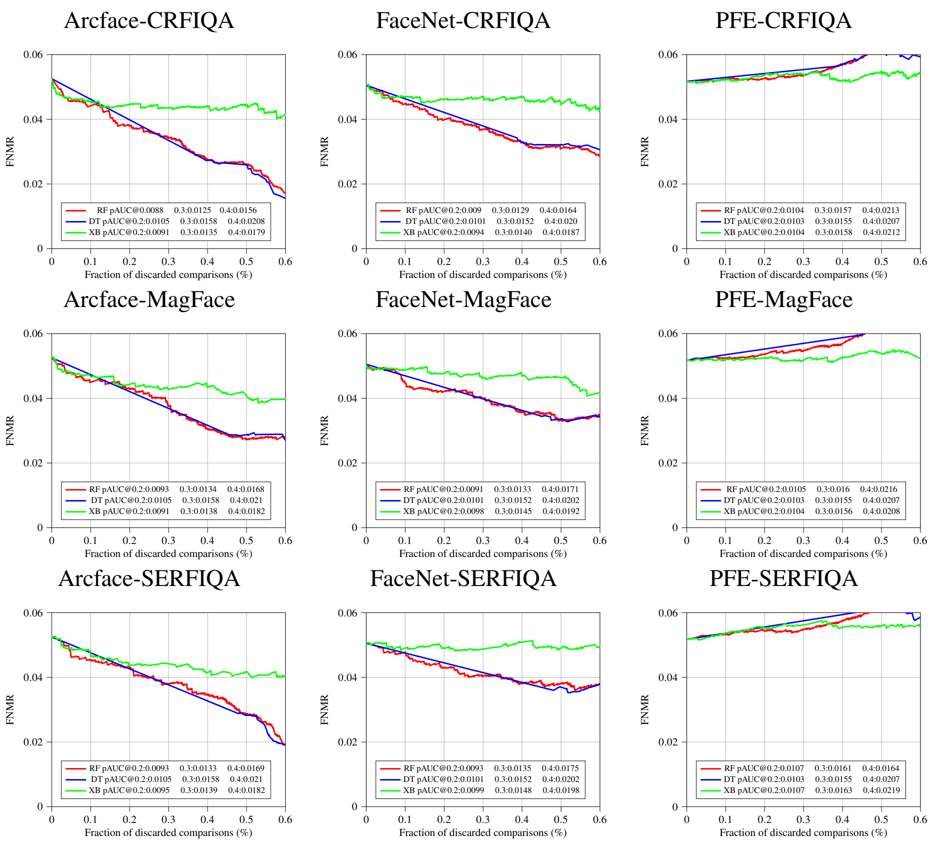


Fig. 5: Performance evaluation of ArcFace, FaceNet, and PFE (left to right) on CRFIQA, MagFace and SERFIQ (top to bottom): EDC and pAUC scores at 0.2, 0.3, and 0.4 discard rates on colorferet dataset.

- Fig 4c shows that the FNMR of the RA, HRF, USF, MCF, SFS, EOS, and IED have similar characteristic upto 40% discard rate before an increase indicating no correlation to utility for color FERET dataset. YA, PA, EOS, HLF, and DSF components on the other hand decrease the FNMR with increased discard ration suggesting a strong correlation of these component measures with utility.

5.4 Results on Unified Score based on Quality Components

As noted previously, we observe varying impact of component quality measures on different datasets. We therefore present the results of our proposed approach of unifying the component scores to one unified score as shown in Fig 5 for ColorFeret dataset [5]. Fig 5 illustrates the EDC curves obtained using three different FRS using three different FIQA. Based on the obtained results, we make the following observations:

- On a general note, we observe that the proposed approach of unifying scores using Decision Tree (DT) and Random Forest (RF) decreases the FNMR with increasing discard ratio. All evaluated supervised methods appear highly effective as a sharp decline in the FNMR can be seen with increasing reject rates with CR-FIQA method performing best across different FRS.
- We further observe ArcFace provides a consistent and low average pAUC score on the color FERET dataset across different FIQA while FaceNet follows a similar trend but relatively lower in performance as compared to ArcFace as FRS.
- While we note the pAUC value of the proposed approach as 0.0088 at 20% discard rate, certain quality measures outperform quality ground truth estimated using CR-FIQA when used with ArcFace the ColorFERET dataset.
- While ArcFace and FaceNet perform well on ColorFERET dataset, PFE FRS tends to perform relatively poorly indicating the need for further investigations.

6 Limitations of our work

Our approach generally scales well on estimating unified score from component quality measures. However, we note that newer FRS architectures such as MagFace and Elastic-CosFace do not contribute in decreasing the FNMR with an increased discard ratio demanding further investigations (See Fig 6 in the supplementary material). In similar lines, Commercial-Off-The-Shelf (COTS) FRS have not been studied in this work. Further, certain inconsistencies in the trend can be observed LFW and XQLFW datasets (illustrated in the supplementary section) as compared to ColorFERET dataset. The inconsistencies can lead to highly inaccurate predictions of quality and this will be investigated in the future works.

[5] Due to the page constraints, we illustrate the result of LFW and XQLFW datasets in the supplementary section.

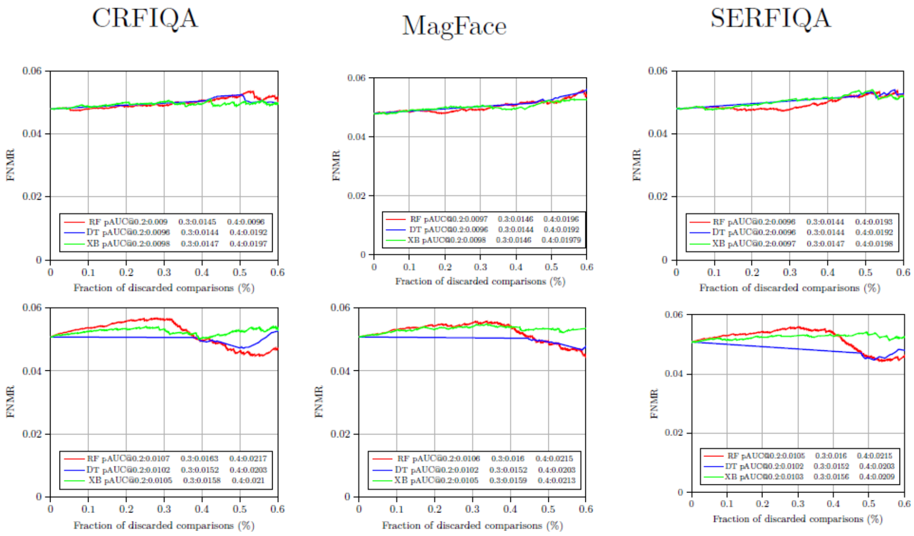


Fig. 6: Limitation of our approach on CRFIQA, MagFace and SERFIQ (left to right) on ElasticFace and MagFace (top to bottom): EDC and pAUC scores at 0.2, 0.3, and 0.4 discard rates on colorferet dataset

7 Conclusion

While the quality components proposed in ISO/IEC CD 29794-5 can measure different quality aspects, it is tedious for a human observer to analyze different values. We presented an efficient method for an unified FIQA score using 21 different component measures proposed in ISO/IEC CD 29794-5. The obtained score, can act as a predictor of FRS performance. The experiments conducted on three different datasets using five different FRS indicate a promising method as it can be observed performance using EDC. However, the invariance of the proposed approach to some recent deep-learning-based FRS architectures remains an open research question and will be studied in future works.

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