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# CR-FIQA: Face Image Quality Assessment by Learning Sample Relative Classifiability

**Fadi Boutros**<sup>1</sup>, Meiling Fang<sup>1,2</sup>, Marcel Klemt<sup>1</sup>, Biying Fu<sup>1</sup>, Naser Damer<sup>1,2</sup>

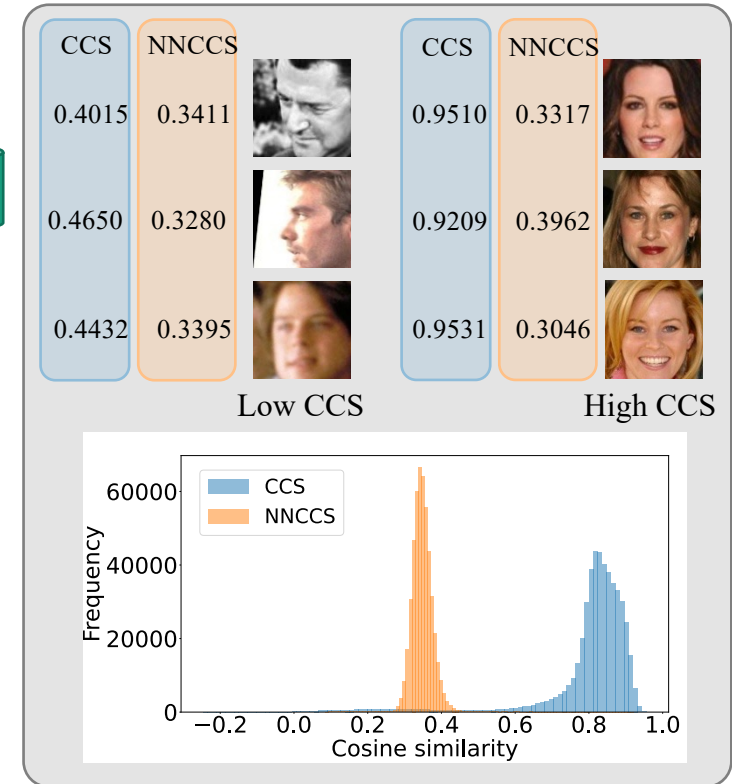
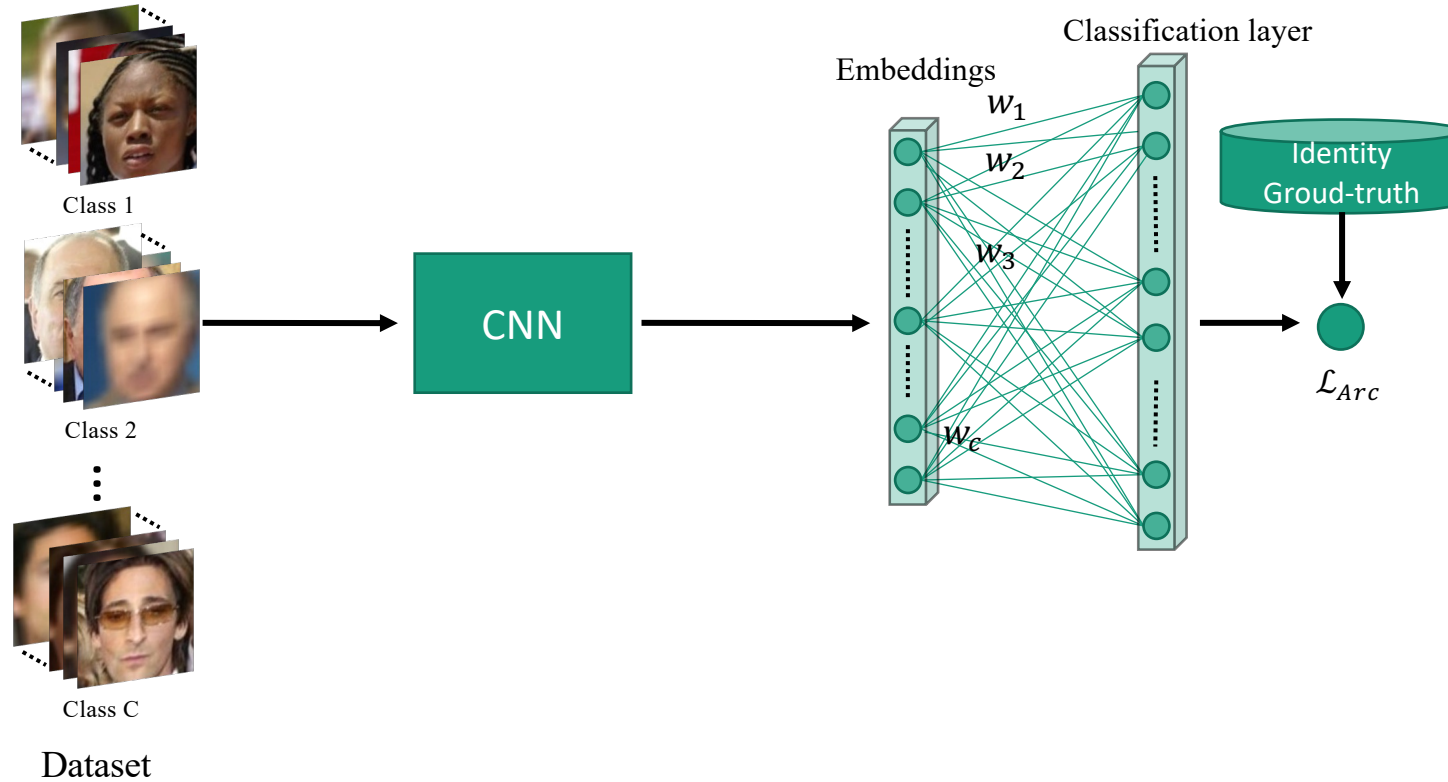
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# CR-FIQA

## Face Image Quality Assessment by Learning Sample Relative Classifiability

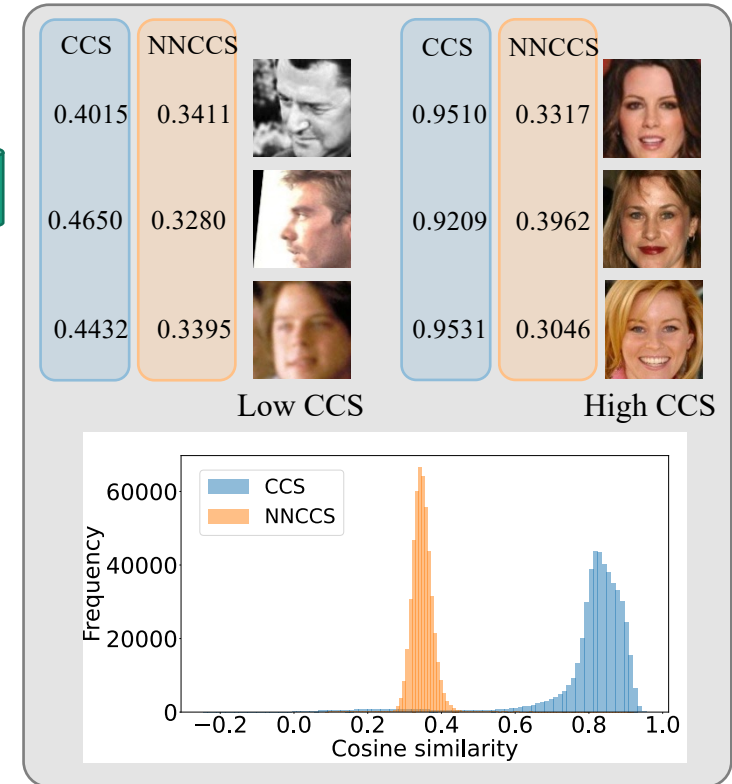
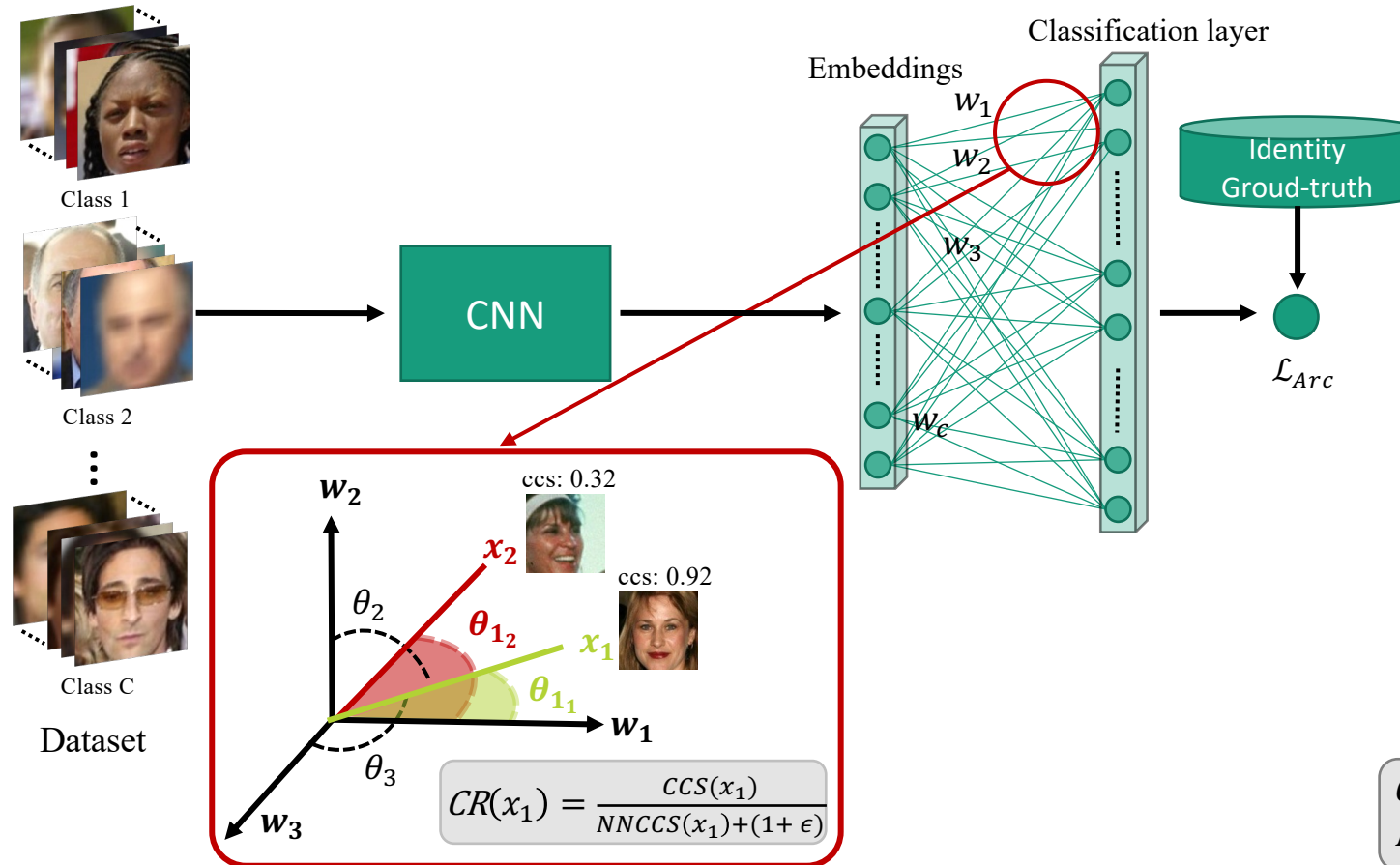


$$CCS(x_1) = \cos(\theta_{1_1})$$

$$NNCCS(x_1) = \max(\cos(\theta_2), \cos(\theta_3), \dots, \cos(\theta_C))$$

# CR-FIQA

## Face Image Quality Assessment by Learning Sample Relative Classifiability



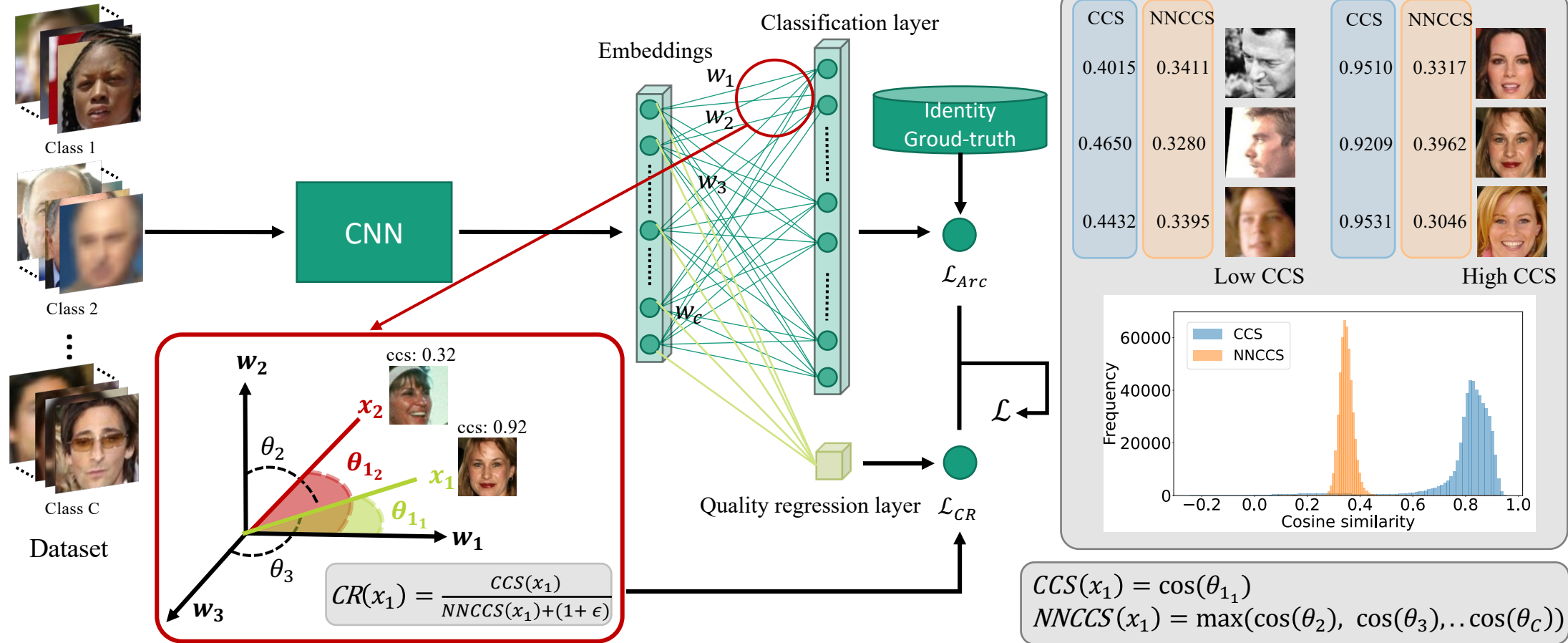
$$CCS(x_1) = \cos(\theta_{11})$$

$$NNCCS(x_1) = \max(\cos(\theta_2), \cos(\theta_3), \dots, \cos(\theta_C))$$



# CR-FIQA

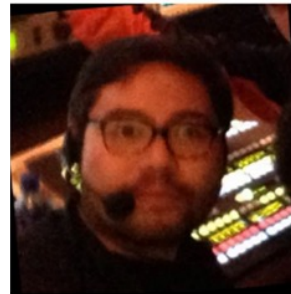
## Face Image Quality Assessment by Learning Sample Relative Classifiability



# What is Face image quality (FIQ)?

- Face image utility indicates the **utility** (value) of an image to **face recognition** (FR) algorithms
- What face quality estimator should answer?

How usable (**utility**\*) is the sample for **automatic face recognition** systems?

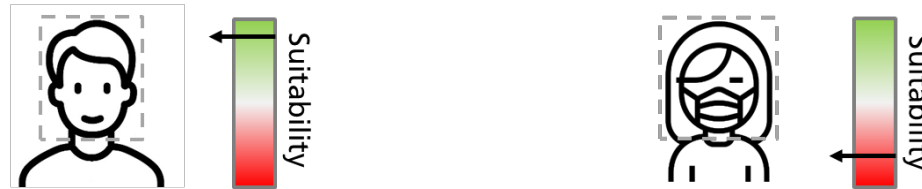


\***Utility**: the observed or predicted positive or negative contribution of an individual sample to the overall performance of a biometric system.

# Why do we need FIQ?

- The performance of biometric recognition is driven by the quality of its samples

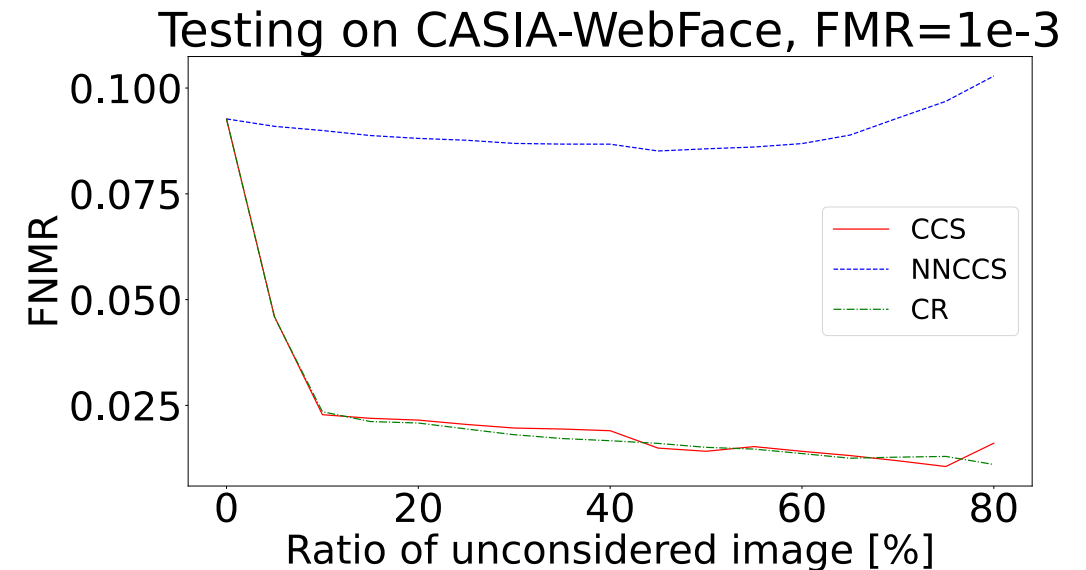
Biometric sample quality: estimate the suitability of a sample for recognition



- Some advantages of sample quality
  - ✓ More robust enrolment
  - ✓ More secure negative identification systems
  - ✓ Enables quality-based fusion approaches

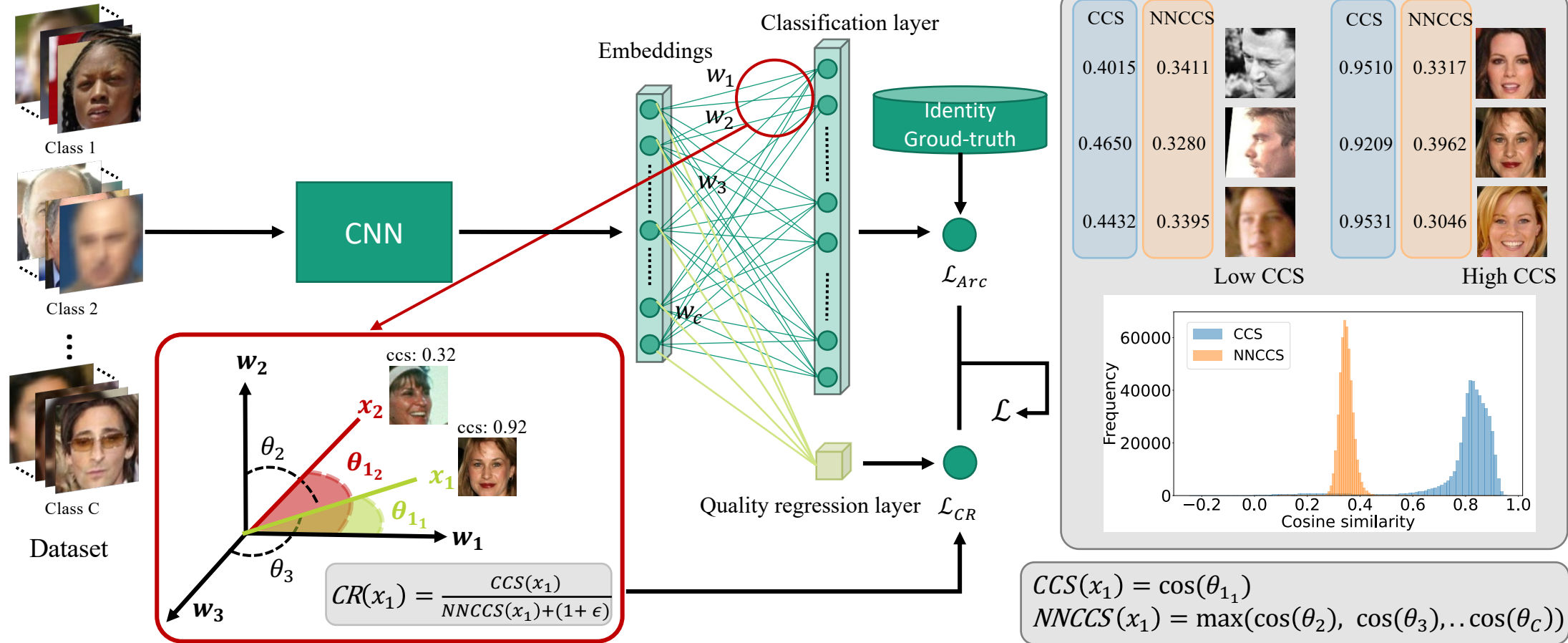
# How can we evaluate face image quality estimator?

- If we removed the worse data (according to our quality estimation), do the face verification/identification performance on the rest of the data (higher quality) enhance?
- Error vs. Reject Curves (ERC): ERC plots the percentage of the neglected data (of the worst estimated quality) vs. a biometric verification/identification error rate.
- Area under the Curve (AUC) of the ERC: provide a quantitative aggregate measure of verification performance across all rejection ratios.



# CR-FIQA

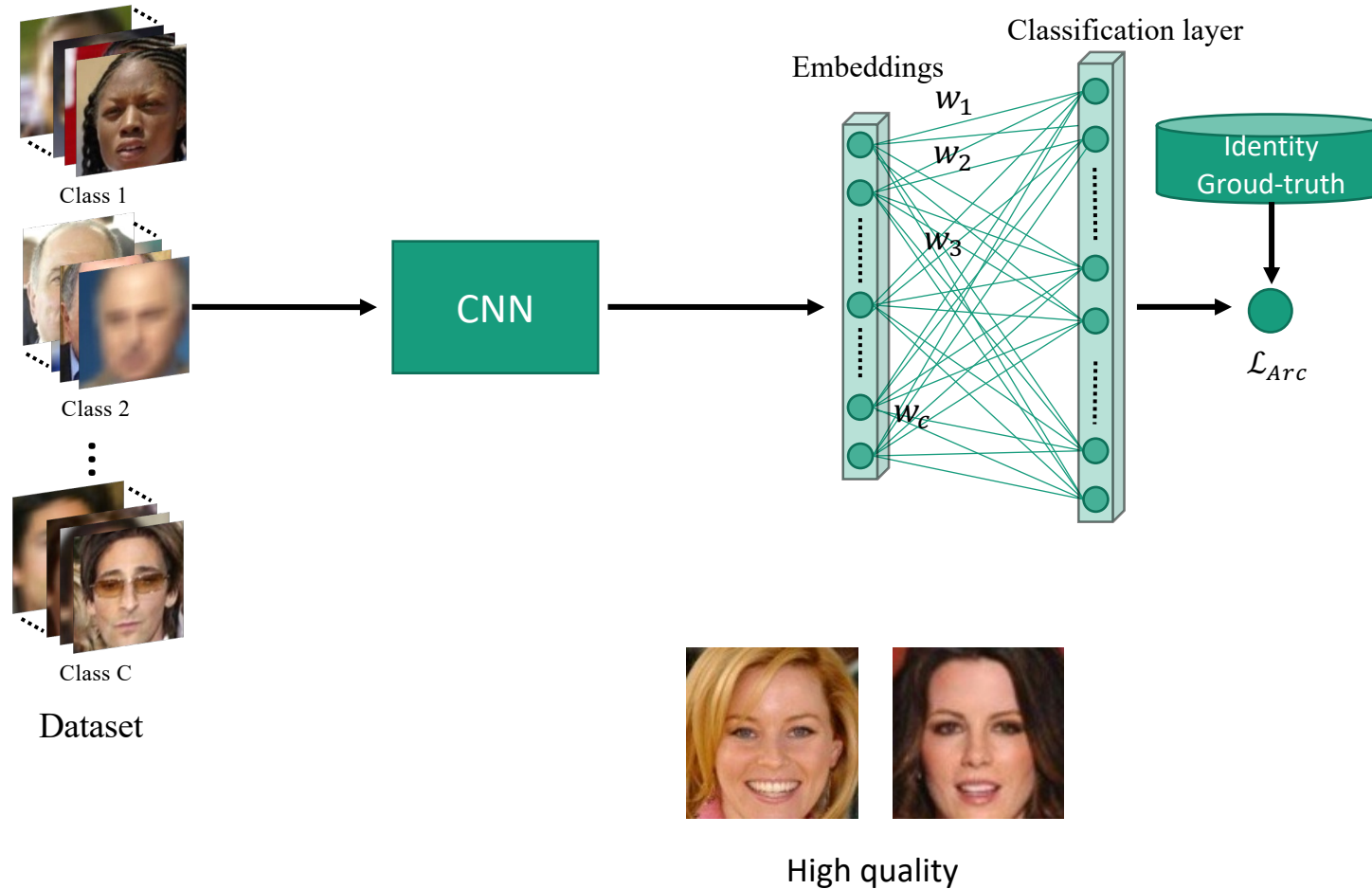
## Face Image Quality Assessment by Learning Sample Relative Classifiability





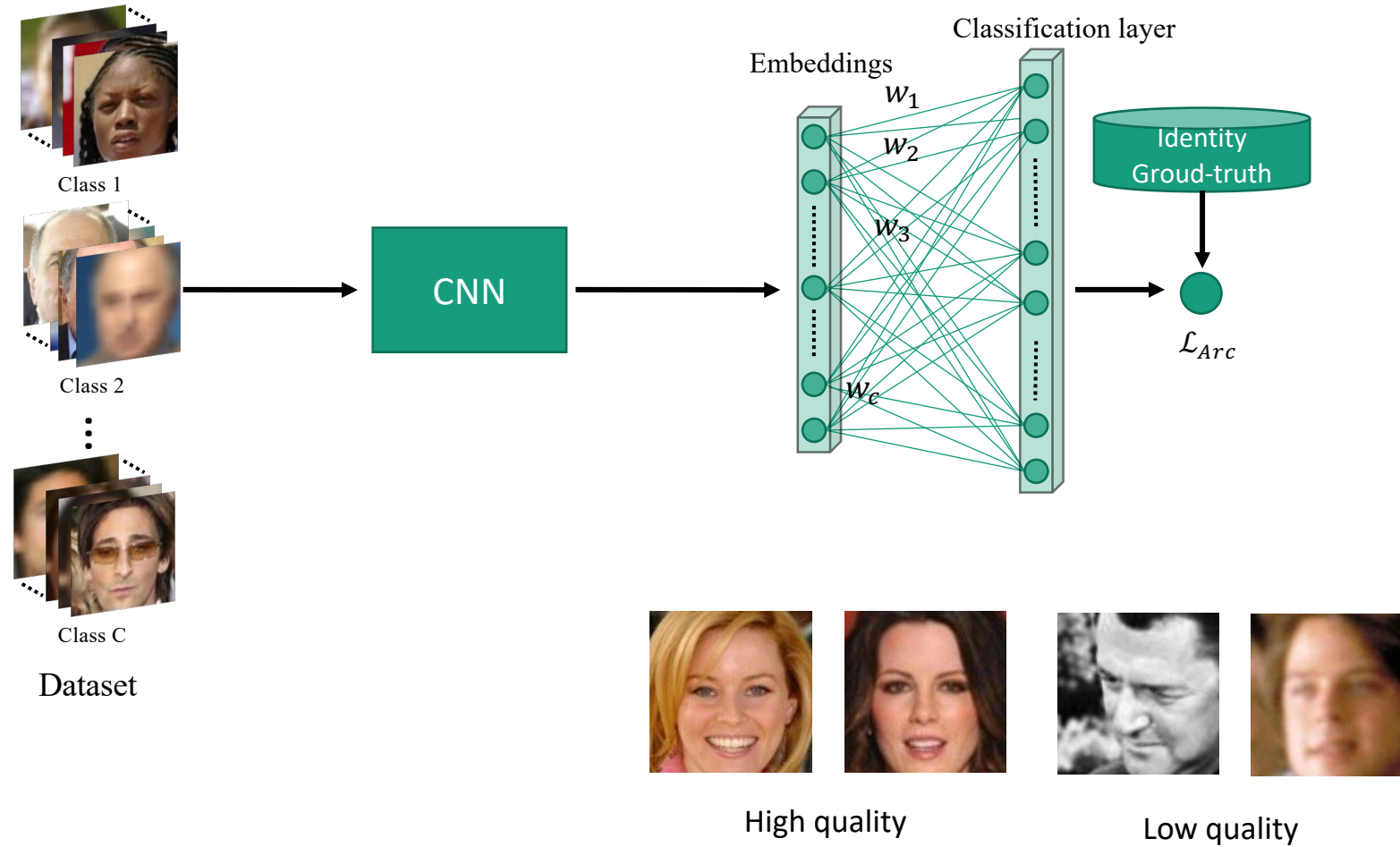
# CR-FIQA

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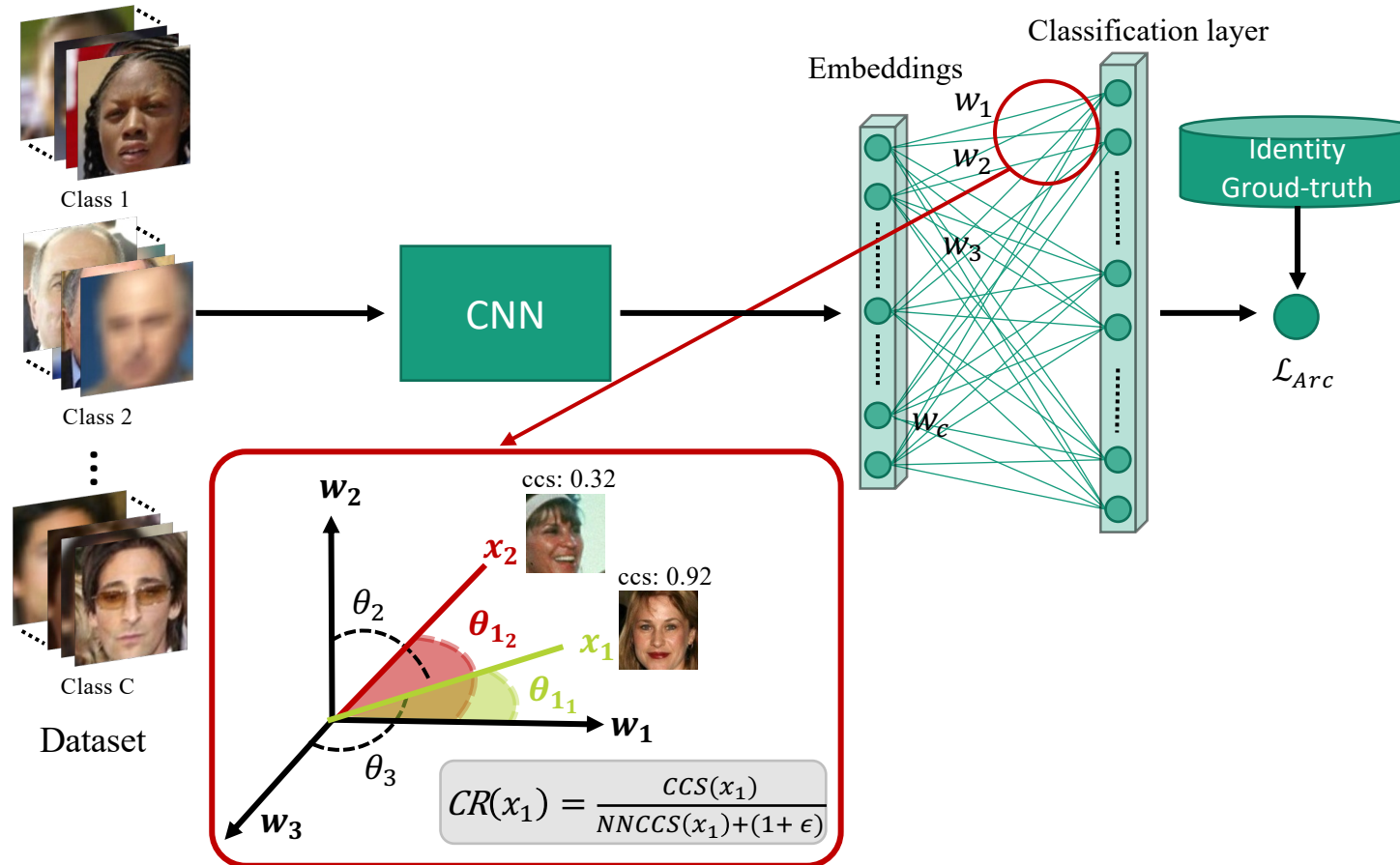
# CR-FIQA

## Face Image Quality Assessment by Learning Sample Relative Classifiability



# CR-FIQA

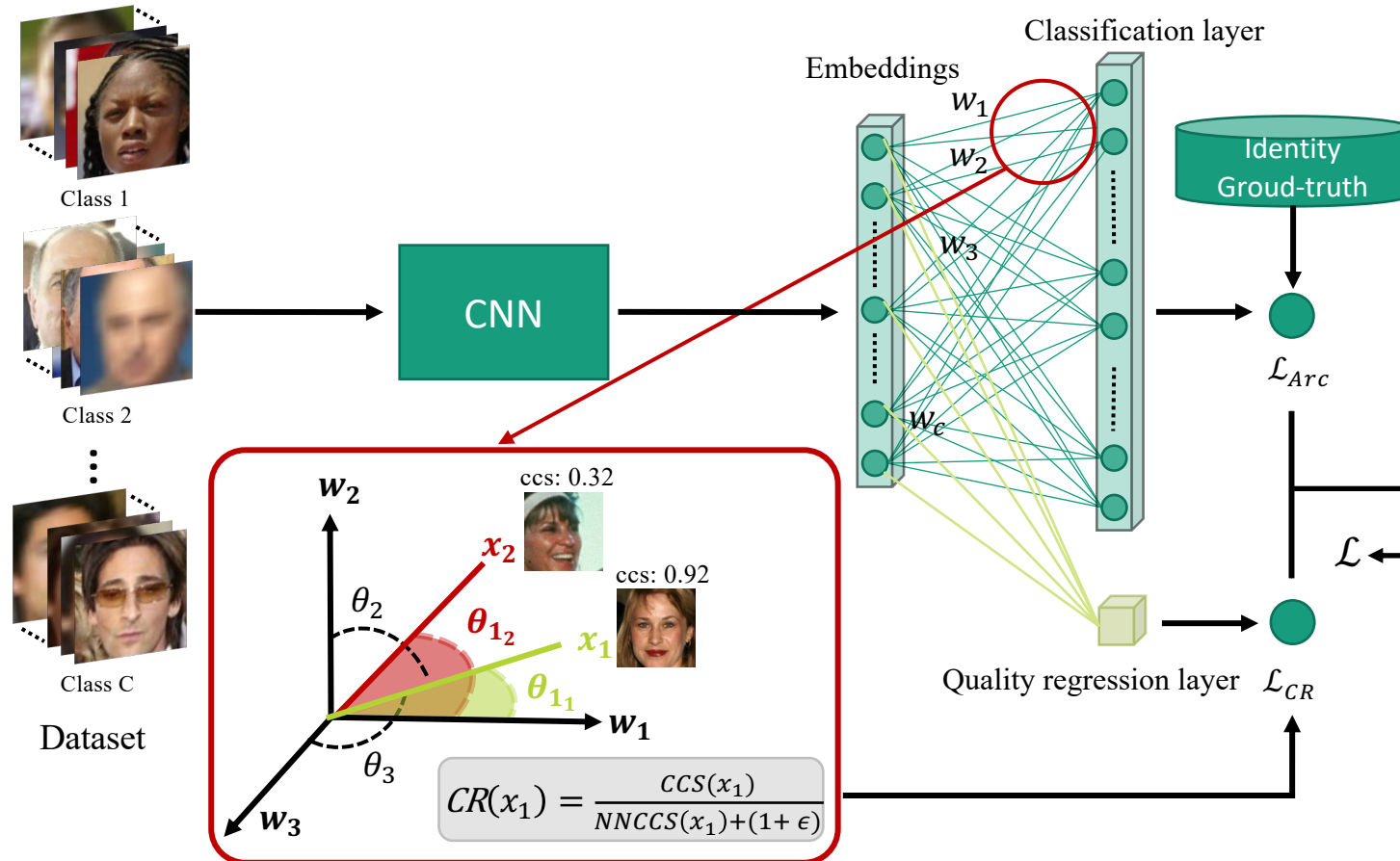
## Face Image Quality Assessment by Learning Sample Relative Classifiability



if a given sample was hypothetically part of the FR model training (which it is not), how relatively close would it be to its class center?

## CR-FIQA

## Face Image Quality Assessment by Learning Sample Relative Classifiability



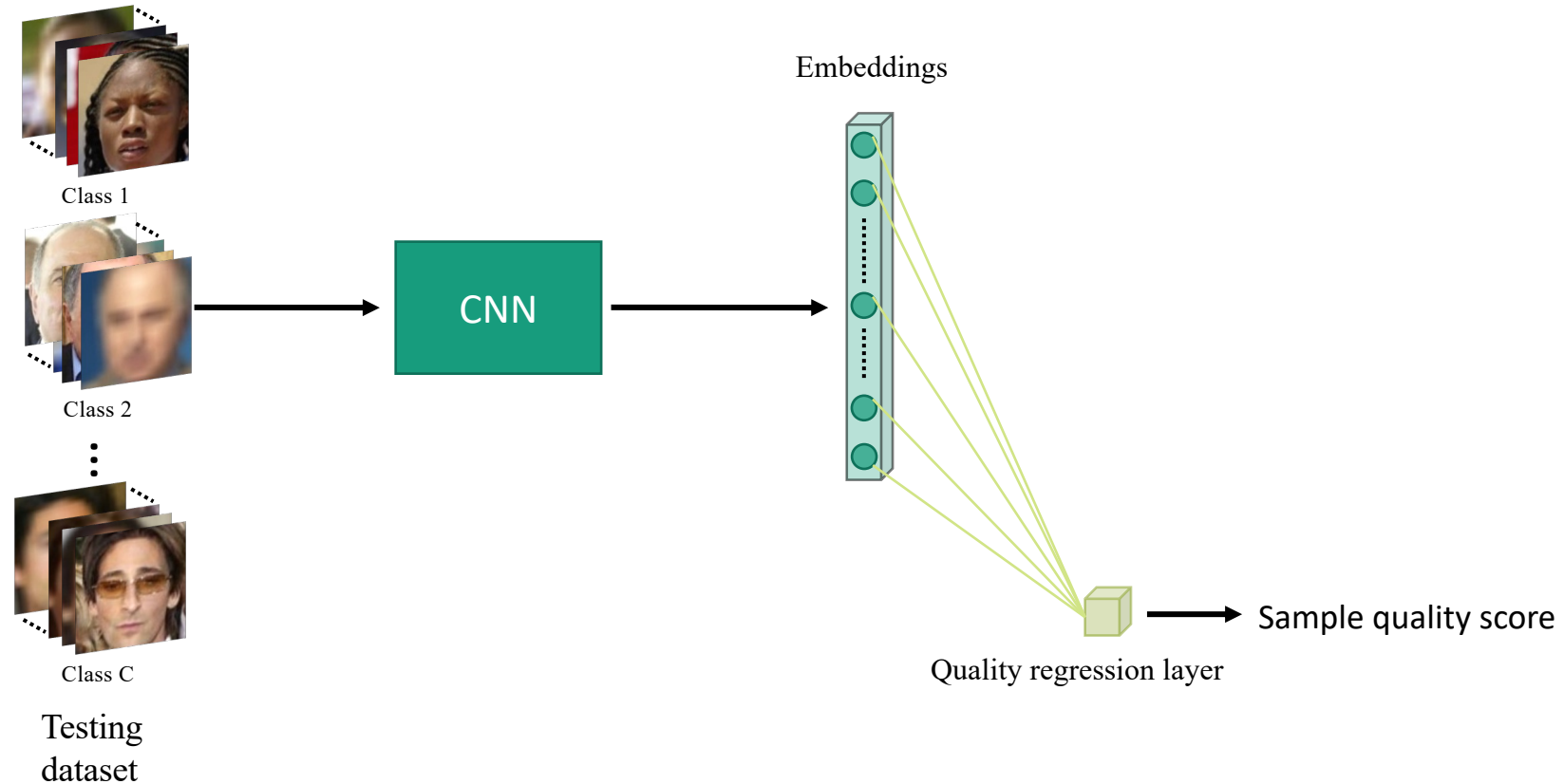
- **CCS** (Class Center Angular Similarity): a proximity between sample  $x$  and its class center
- **NNCCD** (Closest Nearest Negative Class Center Angular Similarity): a proximity between sample  $x$  and the nearest negative class center
- **Certainty Ratio (CR)**: a relative proximity of sample  $x$  to its class center and negative class center

$$CCS(x_1) = \cos(\theta_{11})$$

$$NNCCS(x_1) = \max(\cos(\theta_2), \cos(\theta_3), \dots, \cos(\theta_C))$$

# CR-FIQA

## Face Image Quality Assessment by Learning Sample Relative Classifiability





# CR-FIQA

## Evaluation

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### ➤ CR-FIQA (S)

- Training dataset: CASIA-WebFace
- Base network architecture: ResNet-50

### ➤ CR-FIQA (L)

- Training dataset: MS1MV2
- Base network architecture: ResNet-100

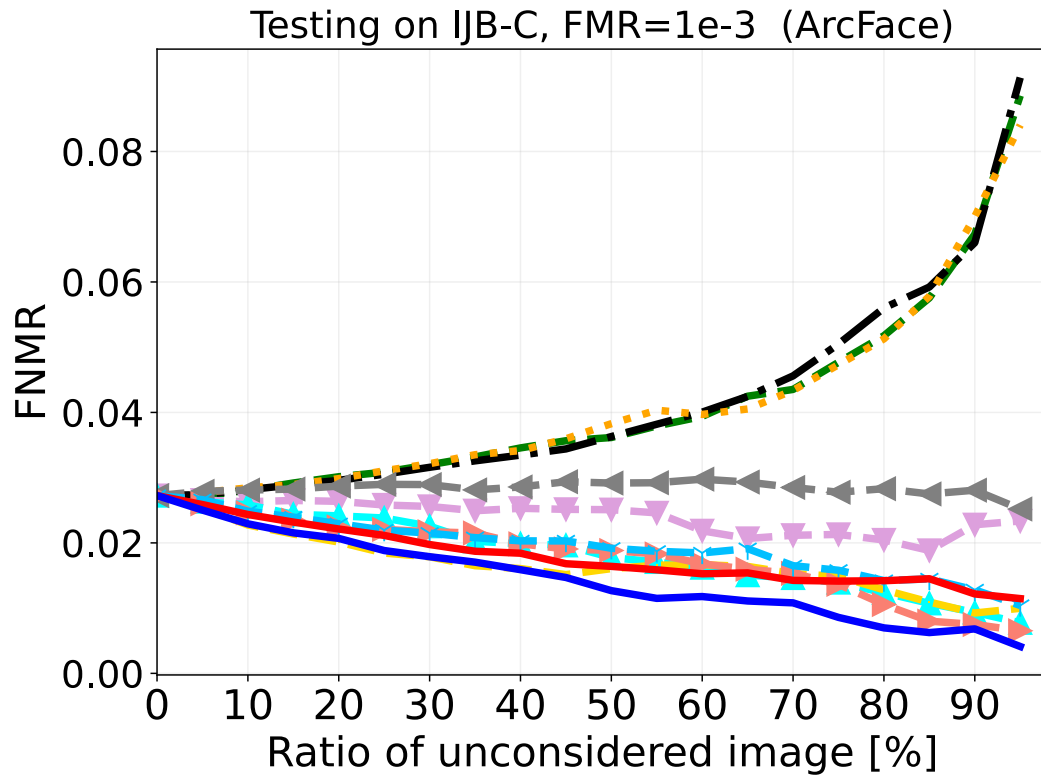
### ➤ Face recognition models

- ElasticFace
- ArcFace
- MagFace
- CurricularFace

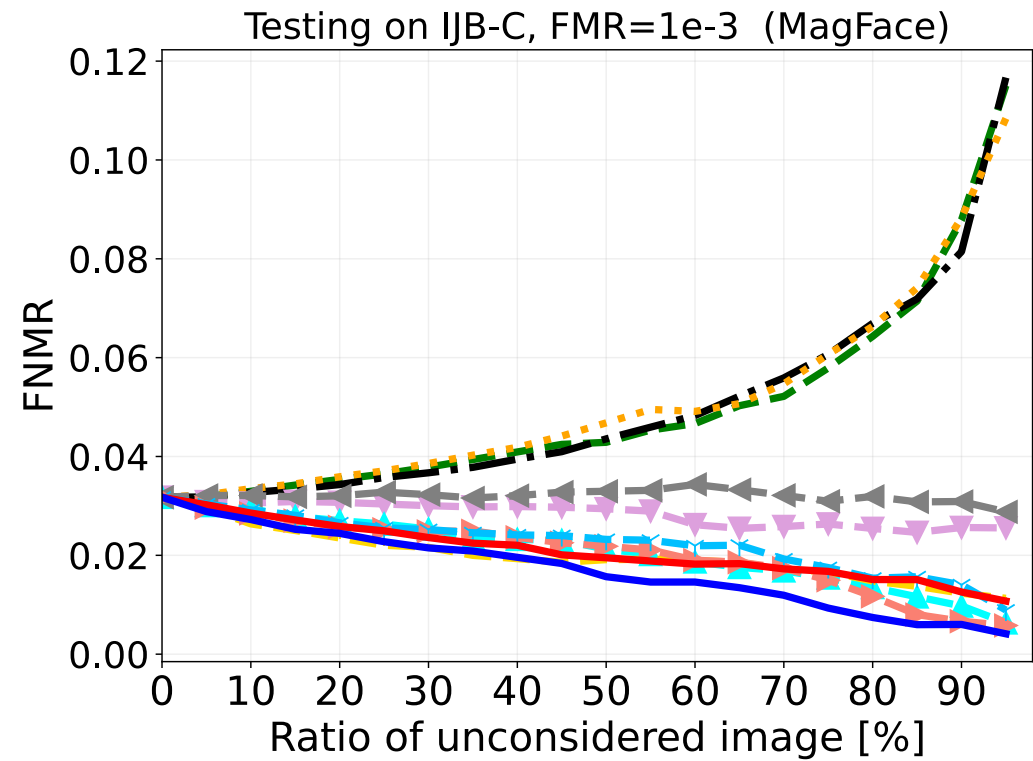
### ➤ Evaluation benchmarks:

- LFW
- AgeDB-30
- CFP-FP
- CALFW
- Adience
- CPLFW
- XQFW
- IJB-C

# CR-FIQA: What did we achieve?



ArcFace



MagFace

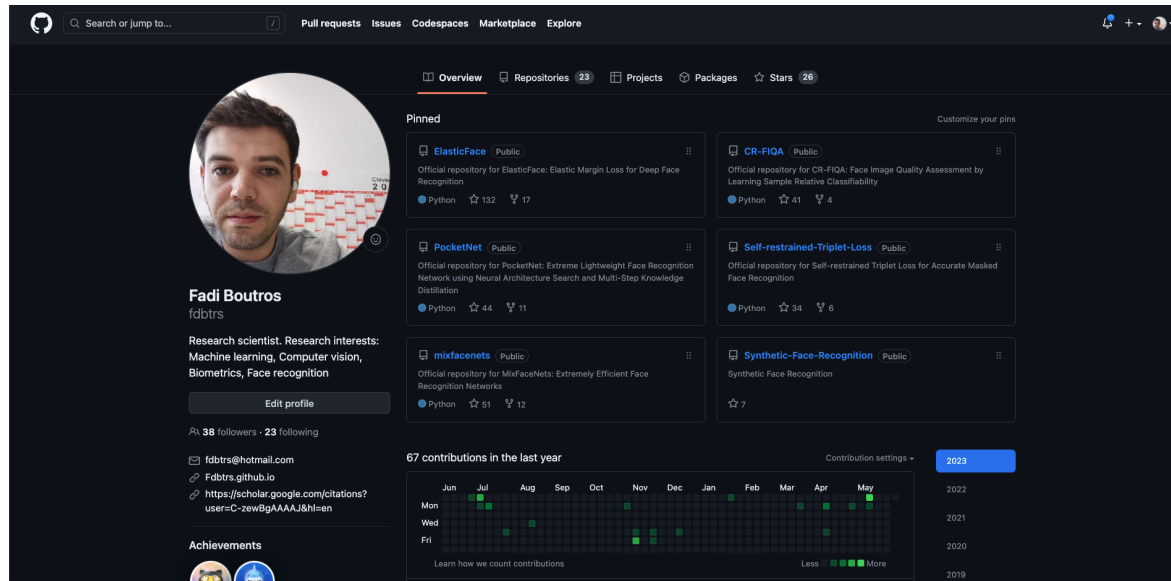


# CR-FIQA: What did we achieve?

Evaluation: quality scores as an embedding weighting term

Quality Estimation		1:1 mixed Verification: TAR (%) at											
		ArcFace [5]			ElasticFace [3]			MagFace [28]			CurricularFace [17]		
		FAR=1e-6	FAR=1e-5	FAR=1e-4	FAR=1e-6	FAR=1e-5	FAR=1e-4	FAR=1e-6	FAR=1e-5	FAR=1e-4	FAR=1e-6	FAR=1e-5	FAR=1e-4
	-	89.85	94.47	96.28	89.15	94.54	96.49	85.67	93.08	96.65	90.46	94.89	96.58
IQA	BRISQUE [29]	86.65	93.62	95.98	85.68	93.51	95.65	81.11	90.64	94.82	88.16	93.98	96.29
	RankIQA [26]	86.37	93.61	95.83	86.71	93.46	96.00	80.78	90.75	94.86	88.16	94.11	96.22
	DeepIQA [2]	81.97	91.64	94.67	78.93	91.59	94.81	73.53	86.34	92.90	82.65	92.04	95.00
FIQA	RankIQ [4]	88.78	94.42	96.20	88.88	94.64	96.45	85.63	92.66	95.70	90.00	94.93	96.53
	PFE [35]	89.50	94.51	96.31	89.10	94.67	96.51	84.93	92.44	95.60	90.36	95.04	96.54
	SER-FIQ [36]	89.74	94.65	96.32	90.05	94.79	96.57	86.02	93.35	95.80	90.66	95.11	96.58
	FaceQNet [14, 15]	87.87	94.04	96.12	86.26	94.09	96.25	82.91	90.56	95.03	89.61	94.65	96.36
	MagFace [28]	89.49	94.41	96.22	89.37	94.69	96.46	85.75	92.71	95.54	90.34	95.02	96.50
	SDD-FIQA [32]	89.39	94.61	96.34	88.07	94.82	96.49	84.69	92.83	95.73	89.91	95.12	96.63
	CR-FIQA(S)(Our)	89.59	<b>94.78</b>	96.35	<b>90.30</b>	<b>94.97</b>	<b>96.63</b>	86.45	93.48	<b>95.95</b>	<b>90.82</b>	<b>95.13</b>	<b>96.64</b>
CR-FIQA(L)(Our)	<b>90.16</b>	94.75	<b>96.36</b>	90.00	94.92	96.58	<b>87.12</b>	<b>93.67</b>	95.90	90.79	95.12	96.58	

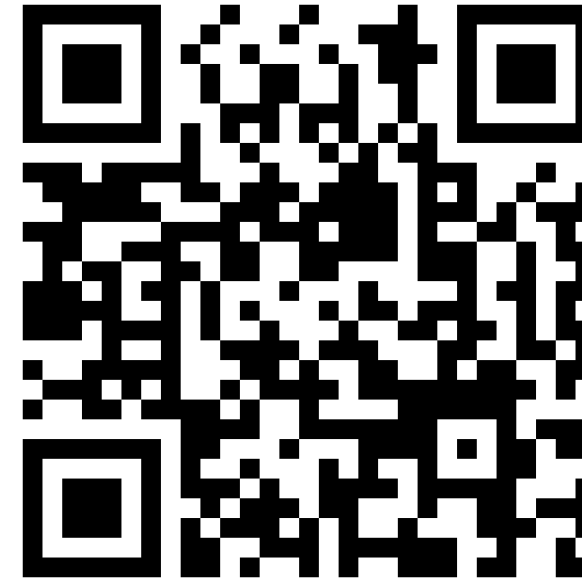
# Code and pretrained models



The screenshot shows the GitHub profile of Fadi Boutros (username: fdbtrs). The profile includes a profile picture, a bio identifying him as a research scientist in machine learning, computer vision, biometrics, and face recognition, and a list of pinned repositories. The pinned repositories are:

- ElasticFace**: Official repository for ElasticFace: Elastic Margin Loss for Deep Face Recognition. 132 stars, 17 forks.
- CR-FIQA**: Official repository for CR-FIQA: Face Image Quality Assessment by Learning Sample Relative Classifiability. 41 stars, 4 forks.
- PocketNet**: Official repository for PocketNet: Extreme Lightweight Face Recognition Network using Neural Architecture Search and Multi-Step Knowledge Distillation. 44 stars, 11 forks.
- Self-restrained-Triplet-Loss**: Official repository for Self-restrained Triplet Loss for Accurate Masked Face Recognition. 34 stars, 6 forks.
- mixfacenets**: Official repository for MixFaceNets: Extremely Efficient Face Recognition Networks. 61 stars, 12 forks.
- Synthetic-Face-Recognition**: Synthetic Face Recognition. 7 stars.

Below the pinned repositories is a contribution graph showing 67 contributions in the last year (2022), with activity concentrated in June, July, and August.



<https://github.com/fdbtrs/CR-FIQA>





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