



Recognition Oriented Iris Image Quality Assessment in the Feature Space

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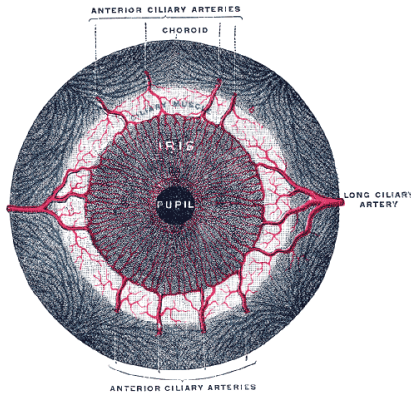
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Outline

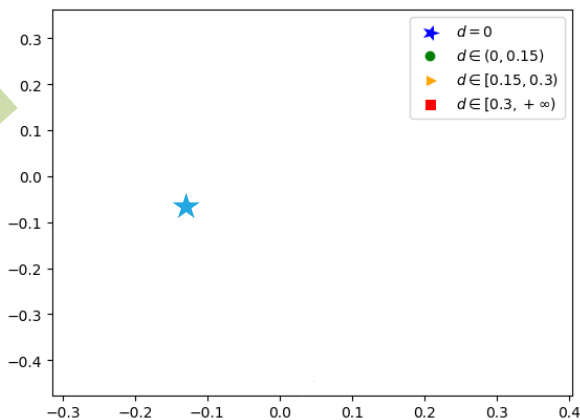
- Main idea
- Comparison with traditional methods
- Dataset & Evaluation criteria
- Experimental result
- Future work

From Iris to Embedding



Iris (anatomy)*

Theoretically

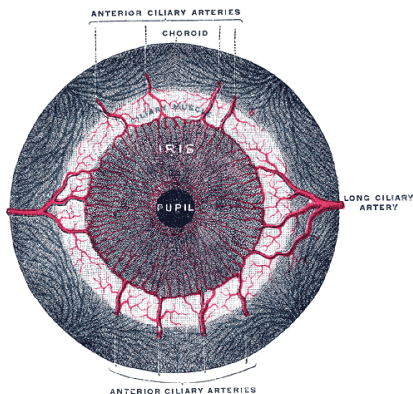


Iris embedding

- Theoretically, for any iris, a unique embedding in the feature space can be obtained through a specific iris recognition system.

• Iris (anatomy)*
• Henry Vandyke Carter and one more author - Henry Gray (1918) Anatomy of the Human Body (See "Book" section below) Bartleby.com: Gray's Anatomy, Plate 878

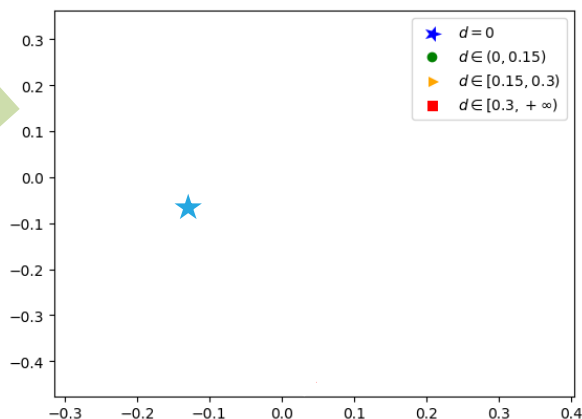
From Iris to Embedding



Iris (anatomy)*

- Feature extractor is a algorithm/program.
- For any input iris image, there must be **an** unique embedding as the output.

Theoretically



Iris embedding

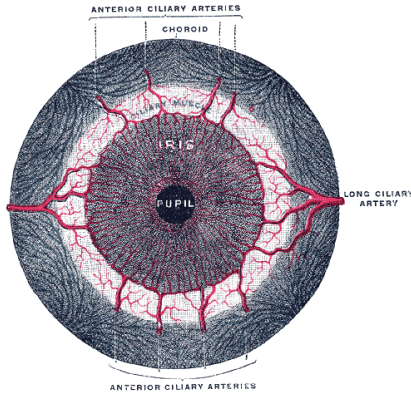


Black Boxes



Iris samples

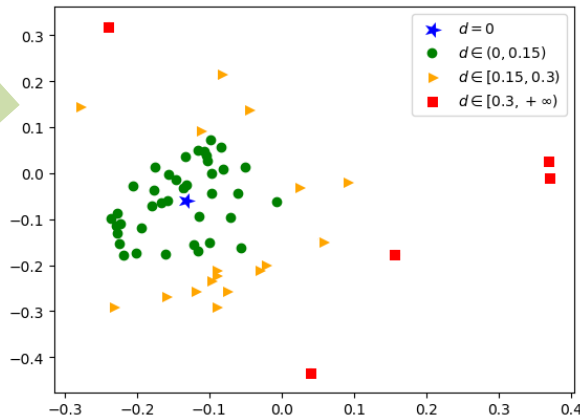
From Iris to Embedding



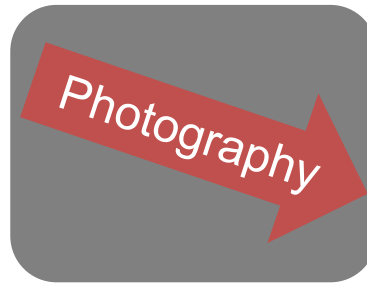
Iris (anatomy)*

- For the same iris, there can be multiple iris images, and each iris image can get an unique embedding through a feature extractor.

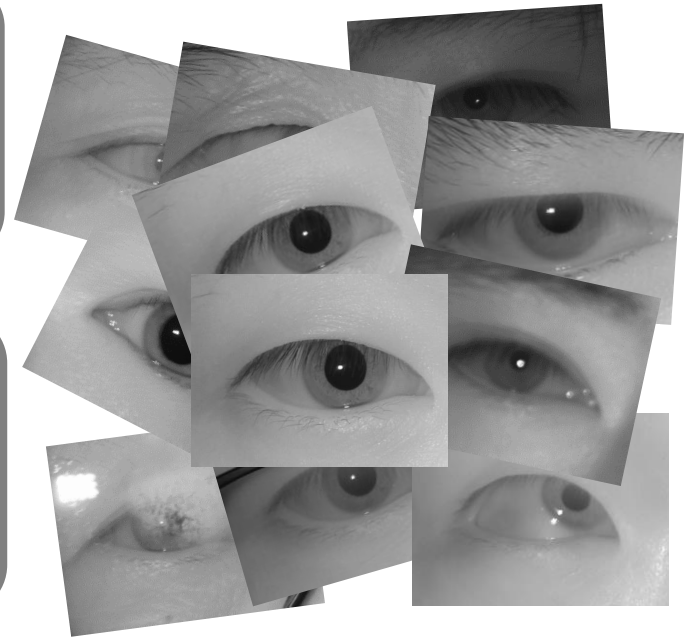
Theoretically



Iris embedding

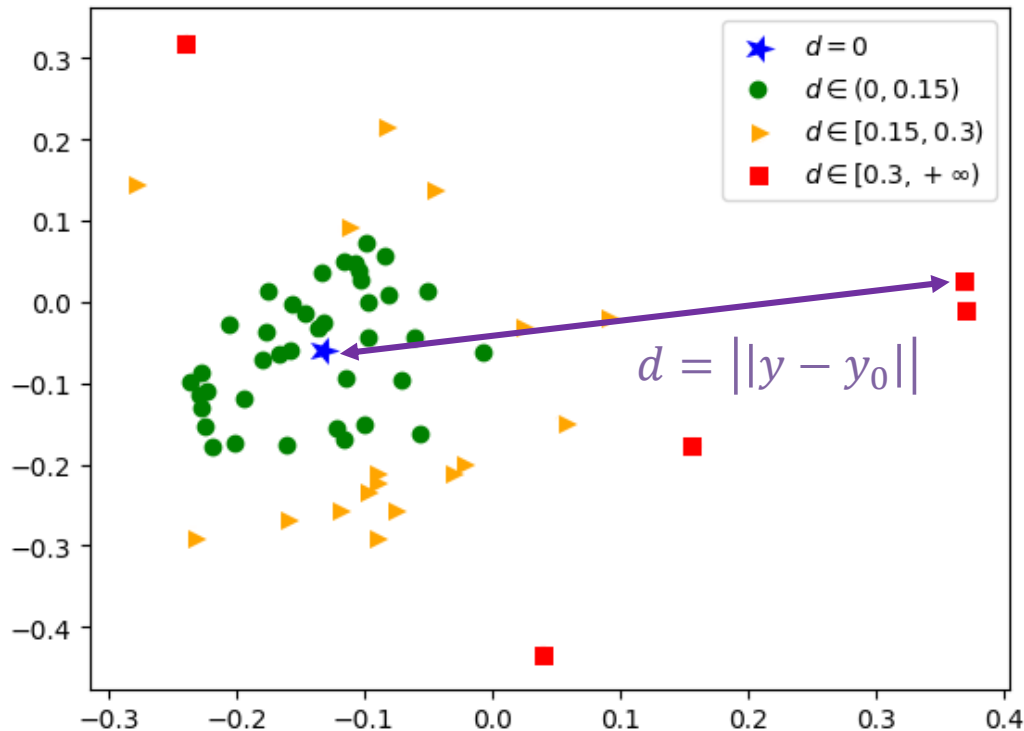


Black Boxes



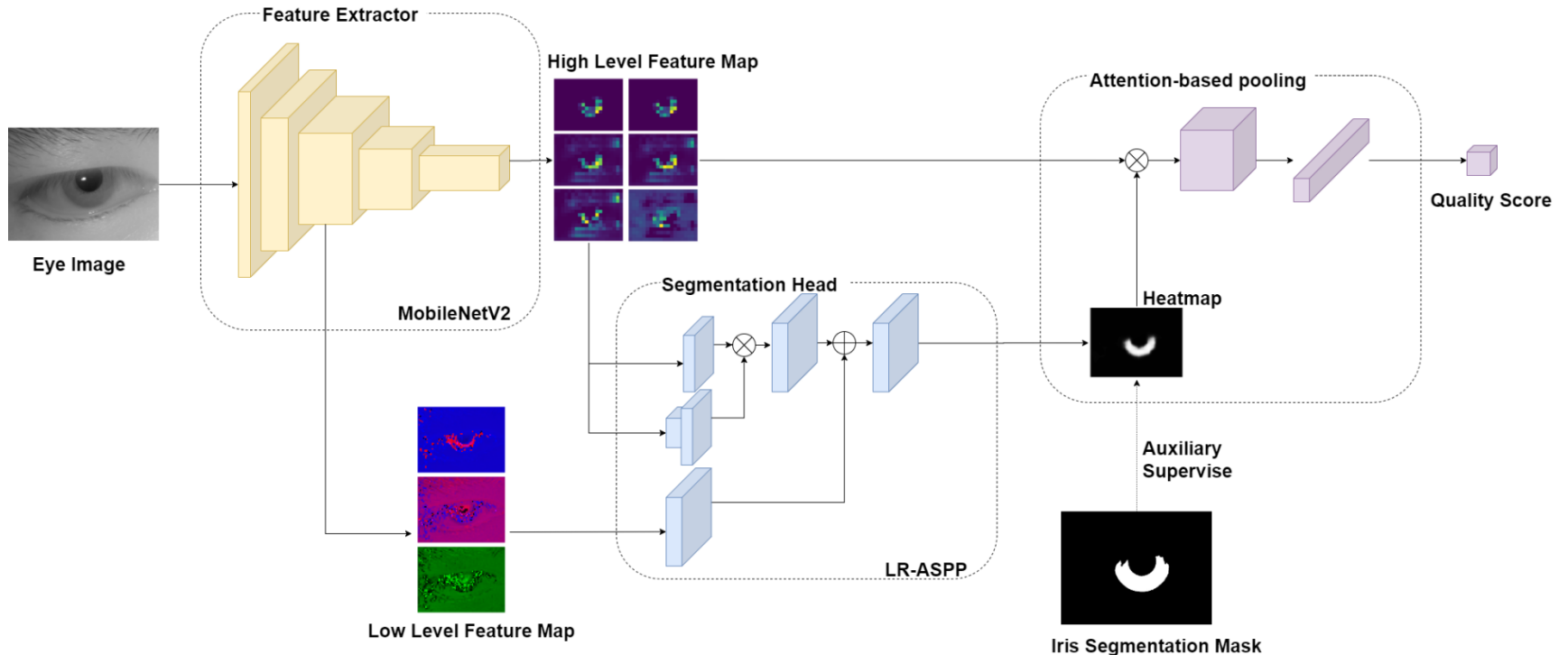
Iris samples

Quality metric: DFS



- **Hypothesis**: the difference between all acquired images and the true iris image are all quality degrade
- The **Distance** between an *embedding of acquired image* and the *true embedding* of in the **Feature Space (DFS)** can be used as **quality metric**.

DFS prediction network

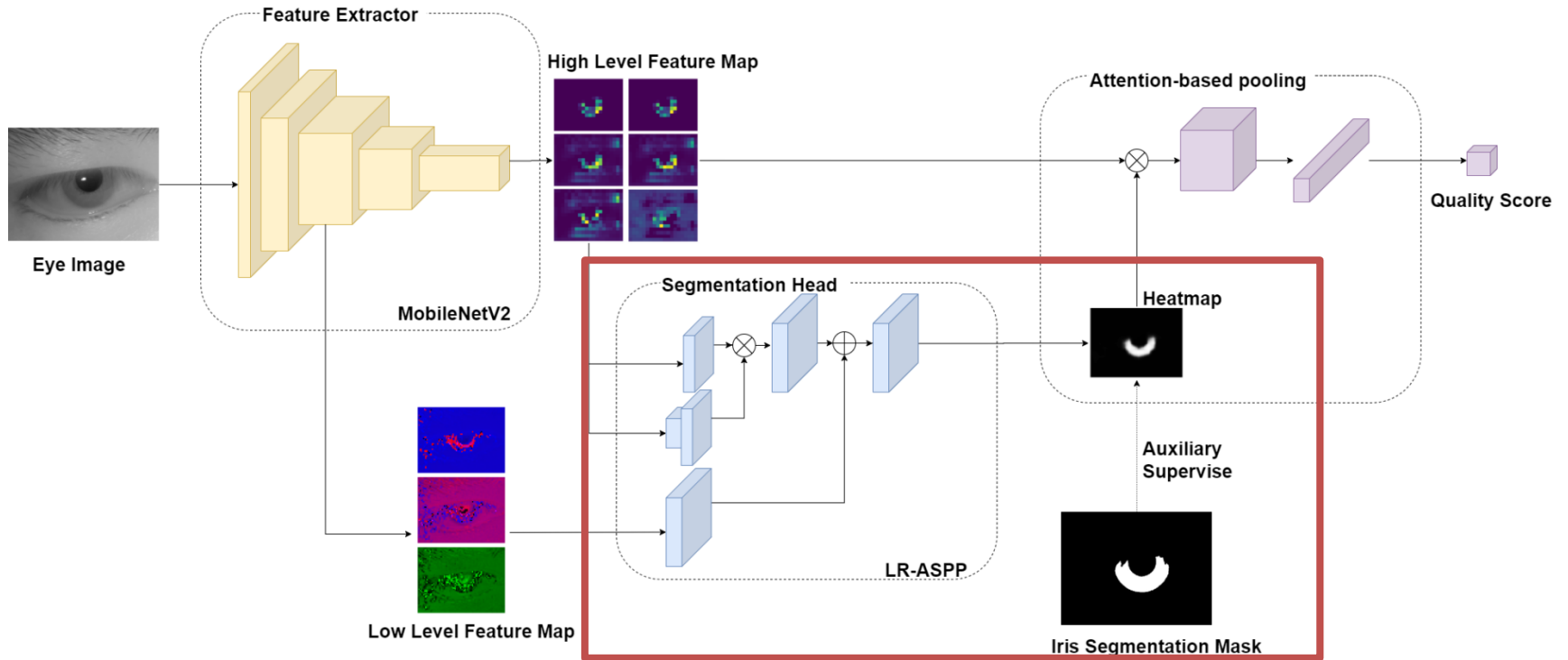


- A deep neural network to directly predict the DFS of the input image and its corresponding true embedding



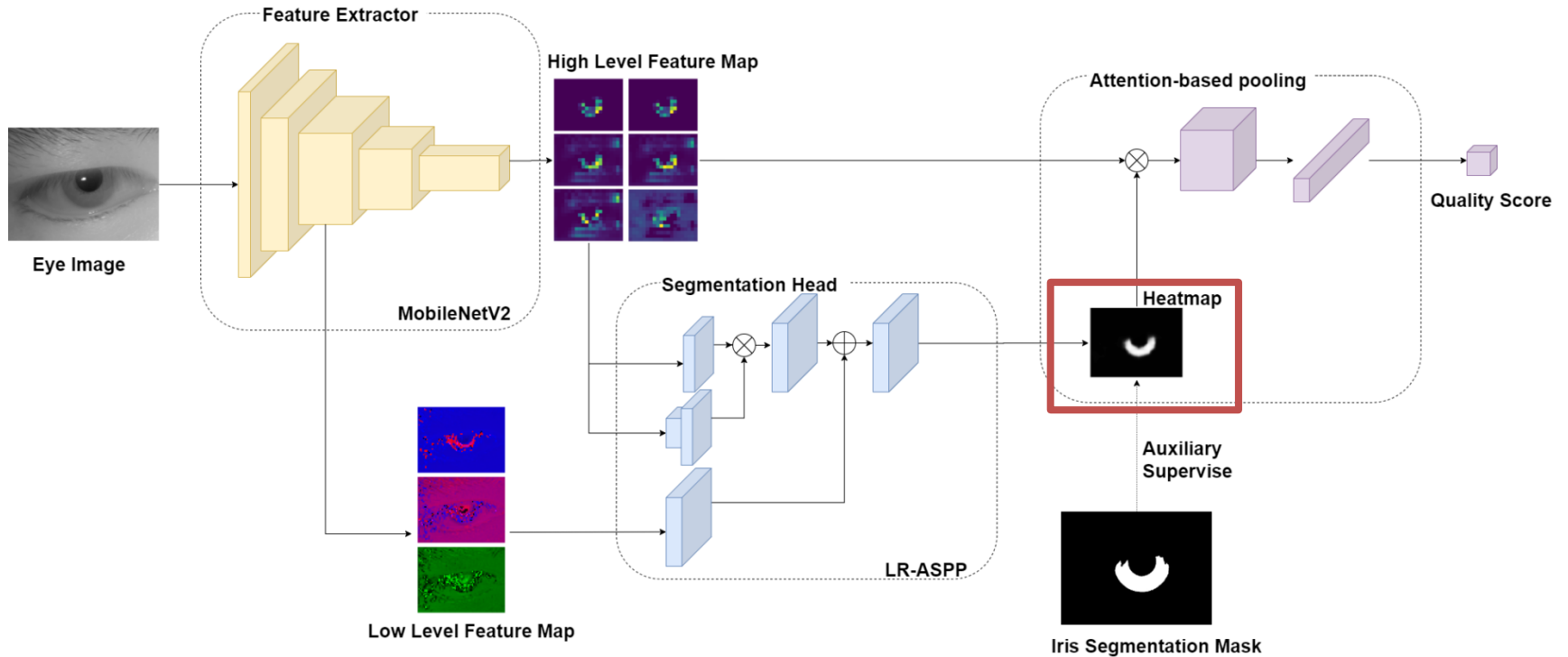
This code is available at
<https://github.com/Debatrix/DFSNet>

DFS prediction network



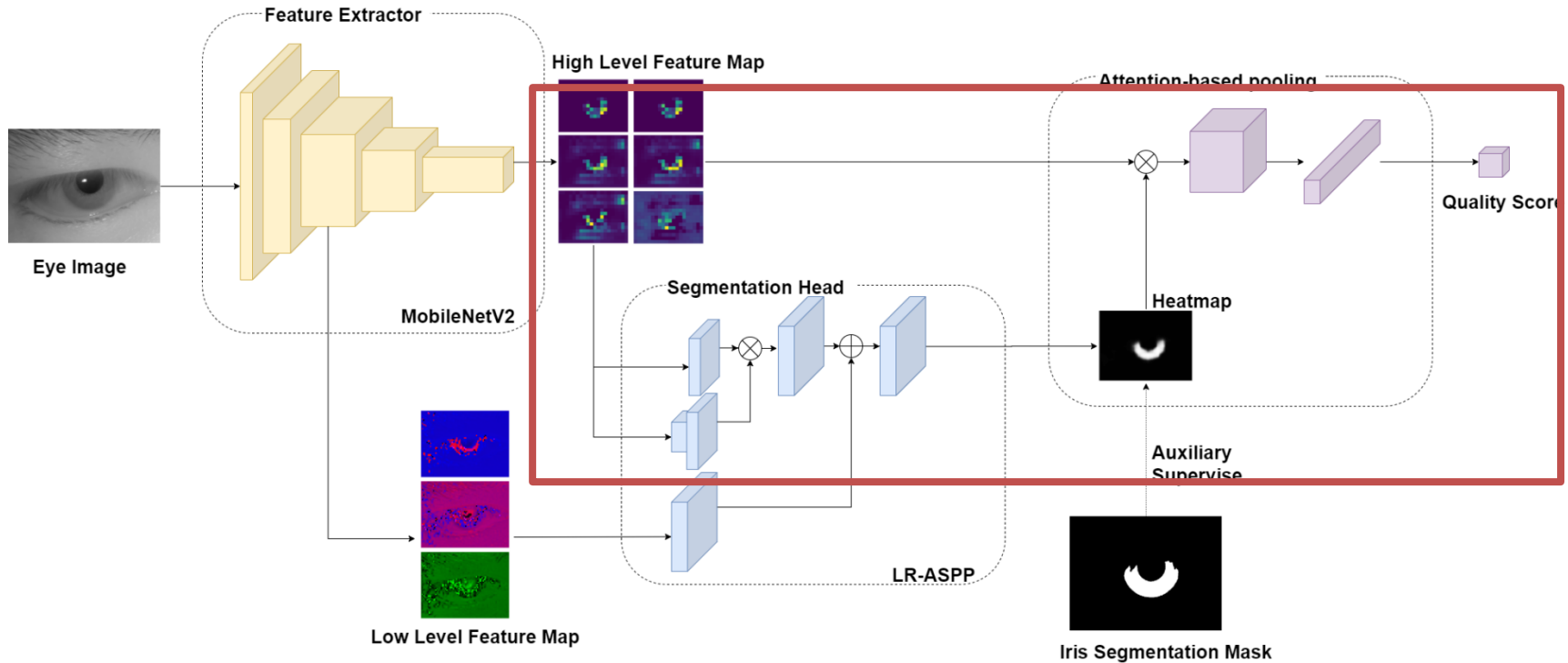
- Segmentation module generate a rough segmentation result as the heatmap required by the attention-based pooling module.

DFS prediction network



- The size of the heatmap is a quarter of the original image, and the value of each pixel represents the probability that the pixel belongs to iris.

DFS prediction network



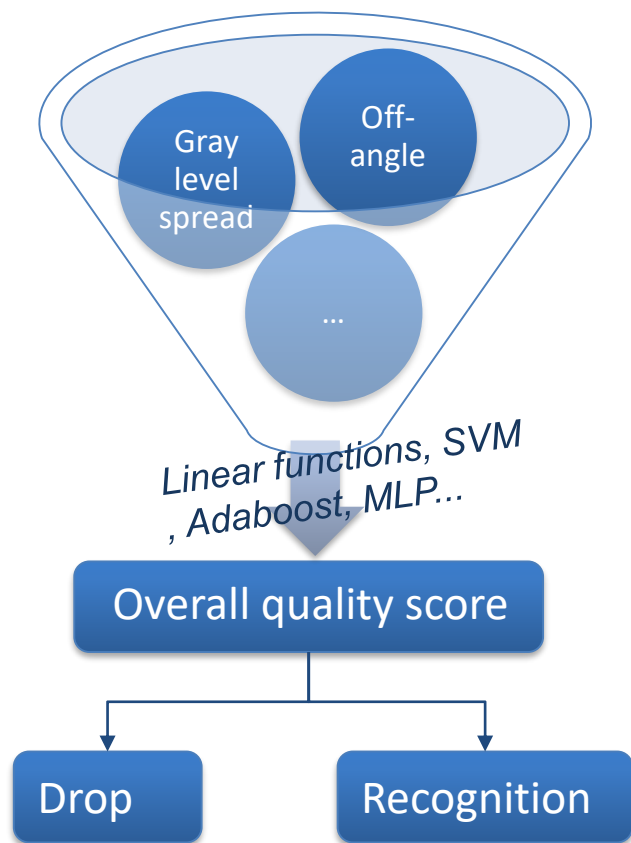
- High-level feature map contains enough information to predict DFS.
- Multiplying high-level features map with heatmap can suppress the response of non-iris regions.

Traditional hand-crafted quality factors

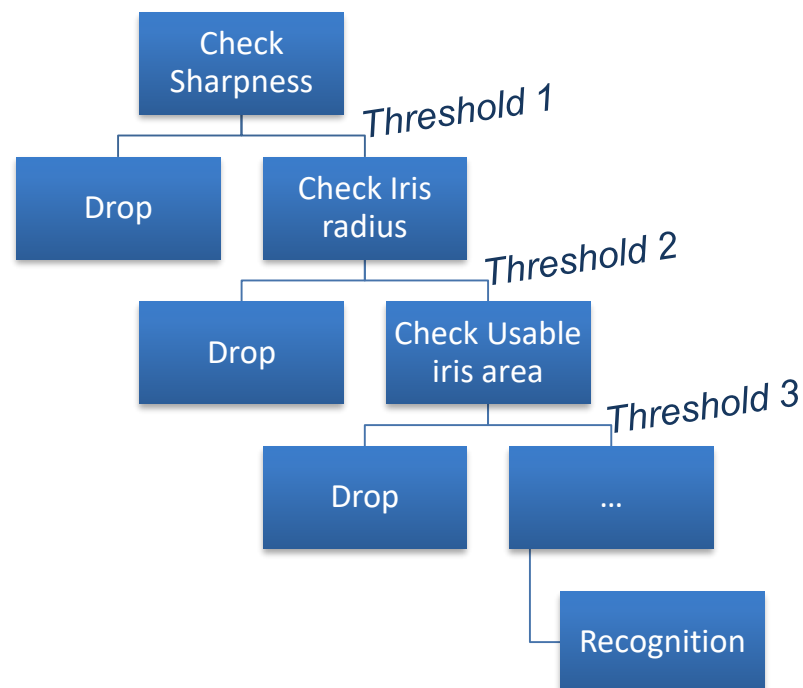
Hand-crafted factor	Impairment
Sharpness	Defocus, Compression
Off-angle	Optical axis of camera and eye not lined up
Usable iris	Occlusion (reflections, eye-wear. etc.)
Gray level spread	Illumination, Saturation
Dilation	Ambient light, Intrinsic

- ISO/IEC 29794-6:2015(E), Information technology — Biometric sample quality — Part 6: Iris image data
- NISTIR, Iris Quality Calibration and Evaluation (IQCE): Evaluation Report

Fusion and multi-step methods

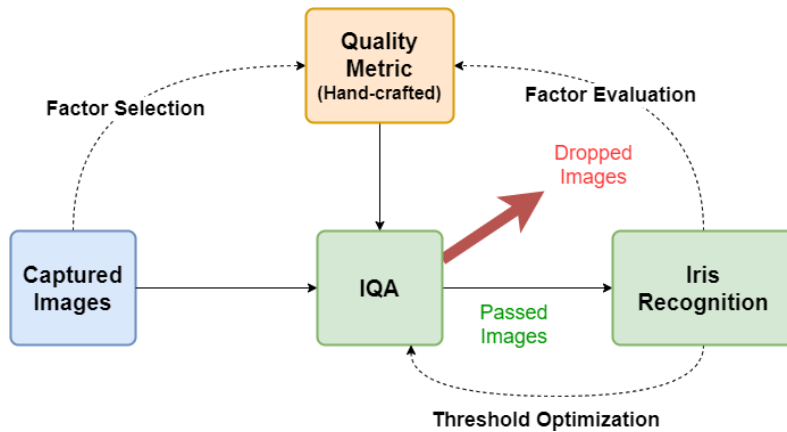


Fusion



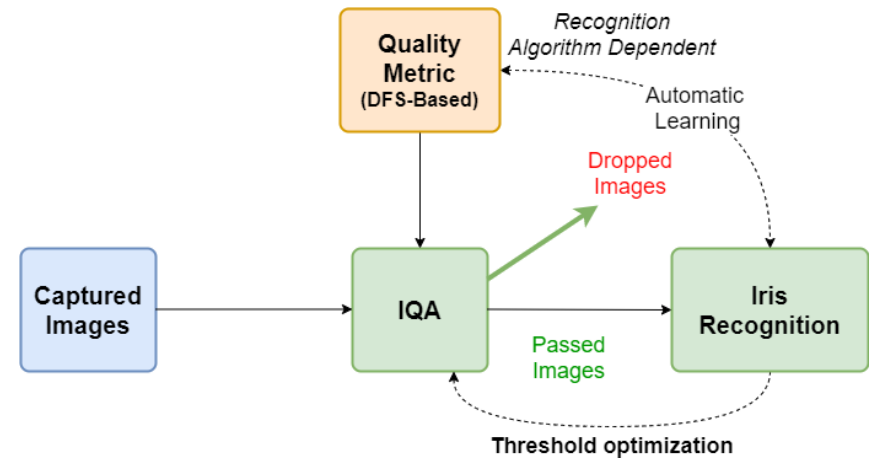
Multi-step

Comparison with traditional methods



Hand-crafted factors based methods

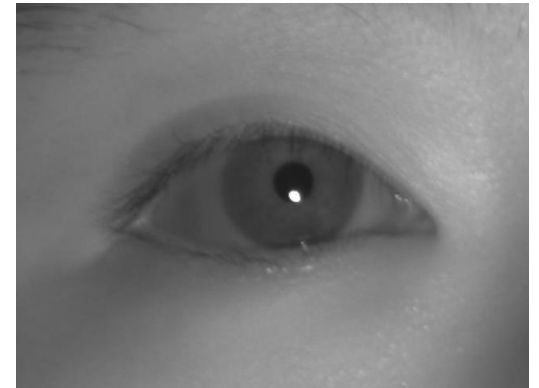
- Complex and separate from recognition



DFS based method

- A trial to bridge the gap between the **image quality assessment** and **biometric recognition**.

Dataset: CASIA-Iris-Complex

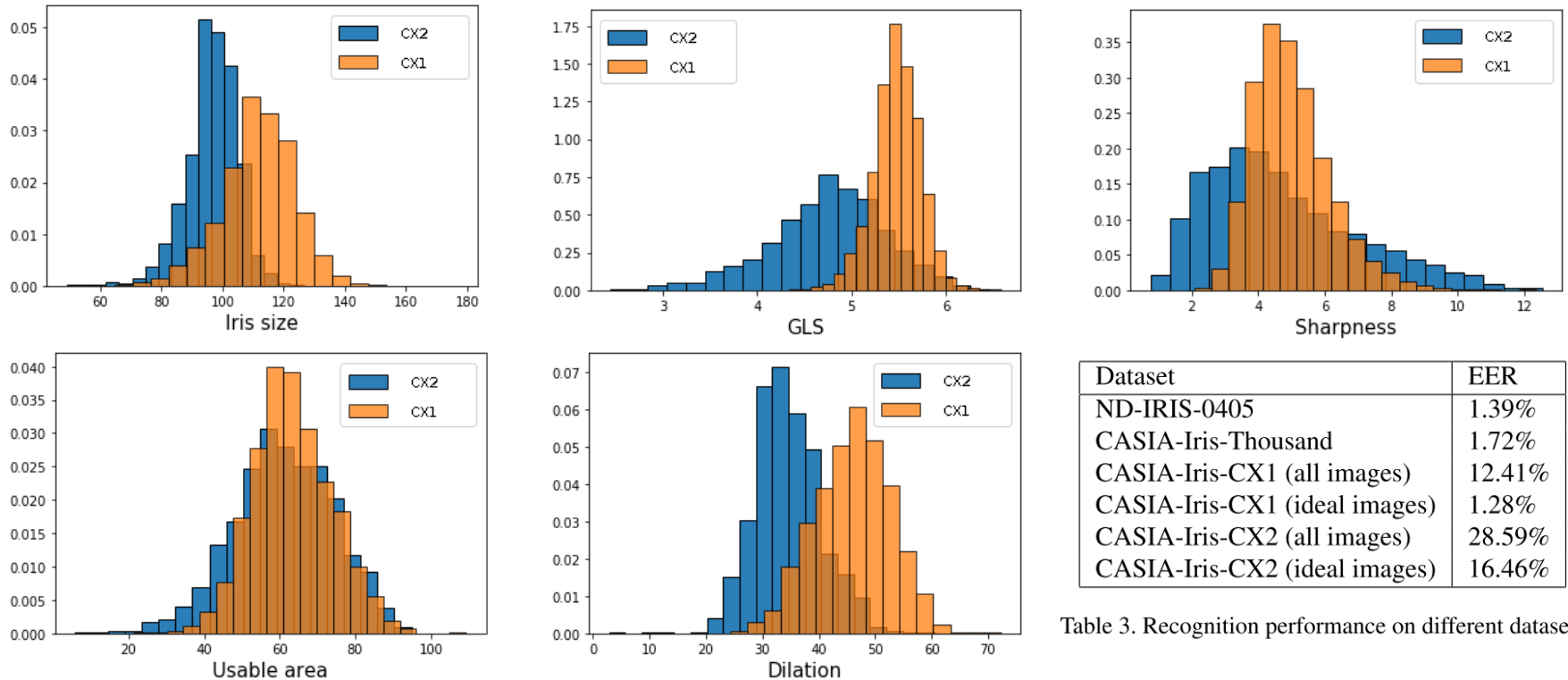


- CX1 (left): Non-cooperative subject
- CX2 (right): Uncontrolled environment & long distance situation



This dataset is available at
www.cripacsir.cn/dataset/casia-iris-complex/

Dataset: CASIA-Iris-Complex



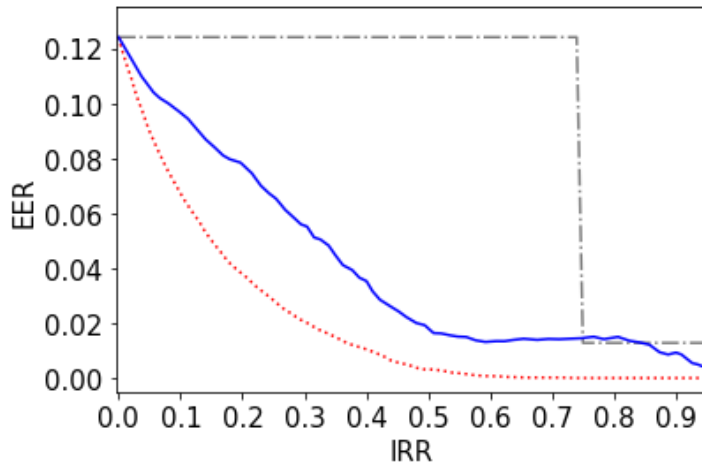
Dataset	EER
ND-IRIS-0405	1.39%
CASIA-Iris-Thousand	1.72%
CASIA-Iris-CX1 (all images)	12.41%
CASIA-Iris-CX1 (ideal images)	1.28%
CASIA-Iris-CX2 (all images)	28.59%
CASIA-Iris-CX2 (ideal images)	16.46%

Table 3. Recognition performance on different datasets

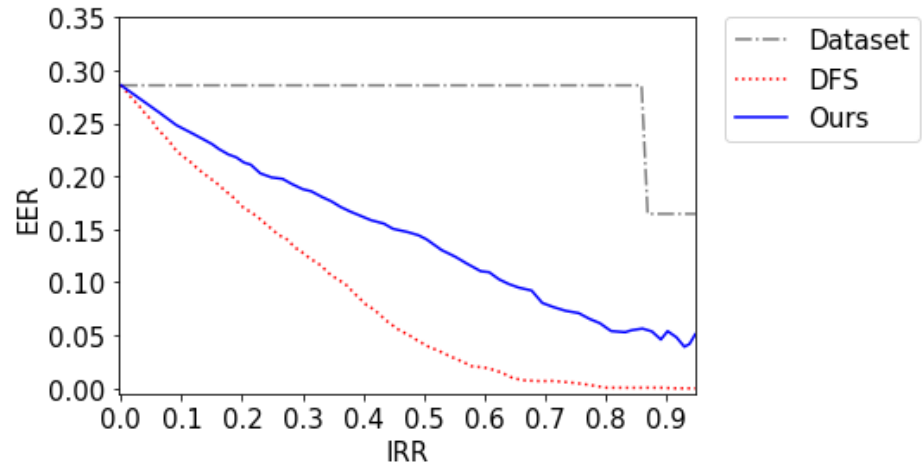
- Fig1-5: Quality score distribution of hand-crafted factors
- Table: Recognition performance on different datasets

- Iris segmentation and recognition algorithms
 - Q. Zhang, H. Li, Z. Sun, and T. Tan. Deep feature fusion for iris and periocular biometrics on mobile devices. *IEEE Transactions on Information Forensics and Security*, 13(11):2897–2912, Nov 2018.
 - C. Wang, Y. Zhu, Y. Liu, R. He, and Z. Sun. Joint iris segmentation and localization using deep multi-task learning framework. *arXiv preprint arXiv:1901.11195*, 2019.

Image Rejection Rate (IRR)



CX1

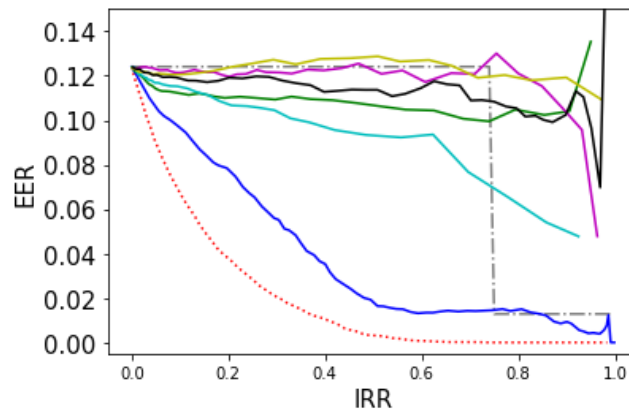


CX3

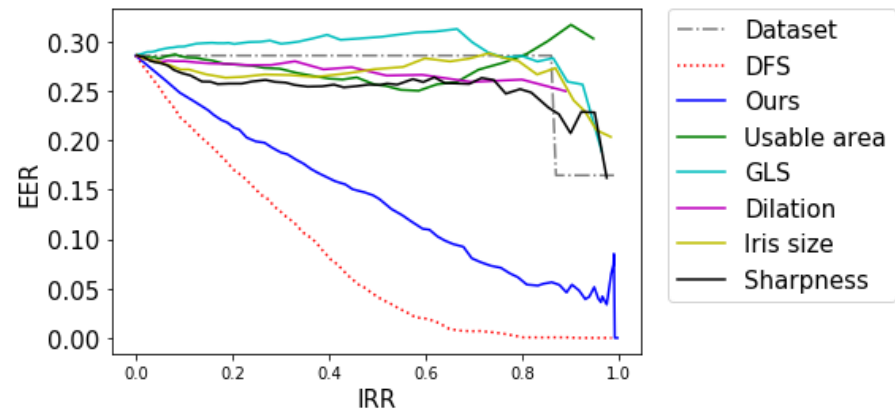
- In an iris recognition system, low-quality images are discarded. The more images that are discarded, the more likely it is to timeout.
- Image rejection rate (IRR) which is related to the possibility of iris recognition system timeout.
- The relationship between IRR and Equal Error Rate (EER) to measure the performance of quality assessment algorithm.

Performance of quality assessment

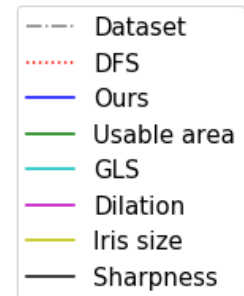
EER@IRR	0		0.25		0.5		0.75		0.95	
dataset	CX1	CX2	CX1	CX2	CX1	CX2	CX1	CX2	CX1	CX2
DFS	12.41	28.5	2.91	15.23	0.31	3.92	0.00	0.56	0.00	0.00
Ours	12.41	28.5	6.52	19.89	1.92	14.06	1.44	7.09	0.40	5.14
Sharpness	12.41	28.5	11.99	25.48	11.40	24.75	10.58	23.48	10.63	25.08
Iris size	12.41	28.5	10.04	26.48	8.67	27.93	6.14	30.00	5.81	27.85
Dilation	12.41	28.5	12.42	26.05	12.81	26.76	13.21	22.79	9.61	17.12
GLS	12.41	28.5	12.68	28.92	13.02	29.27	14.57	27.10	18.21	5.94
Usable are	12.41	28.5	10.93	26.54	11.49	26.88	10.75	27.15	4.68	32.29



CX1



CX3



Conclusions

- Embeddings distance in feature space (DFS)
- DFS prediction network
- Dataset: CASIA-IRIS-Complex
- Image rejection rate (IRR)

THANK YOU

Suggestions Questions