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Recognizability Embedding Enhancement for Very Low-Resolution Face Recognition (VLRFR) and Quality Estimation

Jacky Chen Long Chai, Tiong-Sik Ng, Cheng-Yaw Low, Jaewoo Park, Andrew Beng Jin Teoh

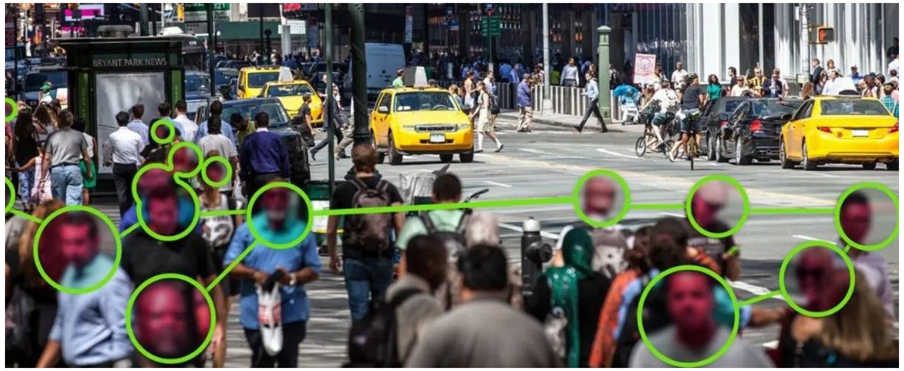
YONSEI UNIVERSITY

MSL Multimedia Security Lab

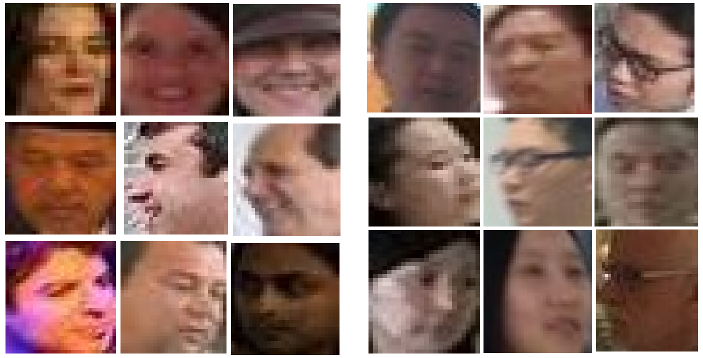
ibs Institute for Basic Science

Introduction

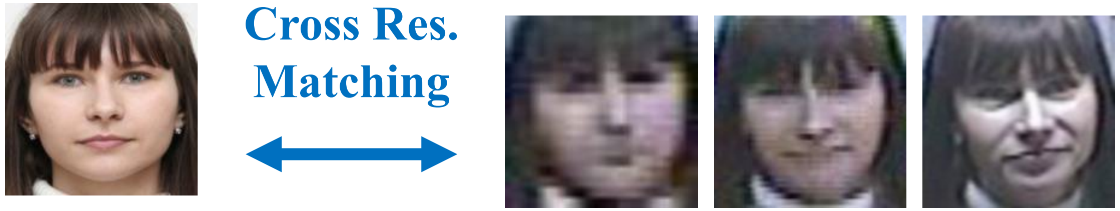
- Region of interest become smaller due to extreme stand-off distance or broad viewing angle.



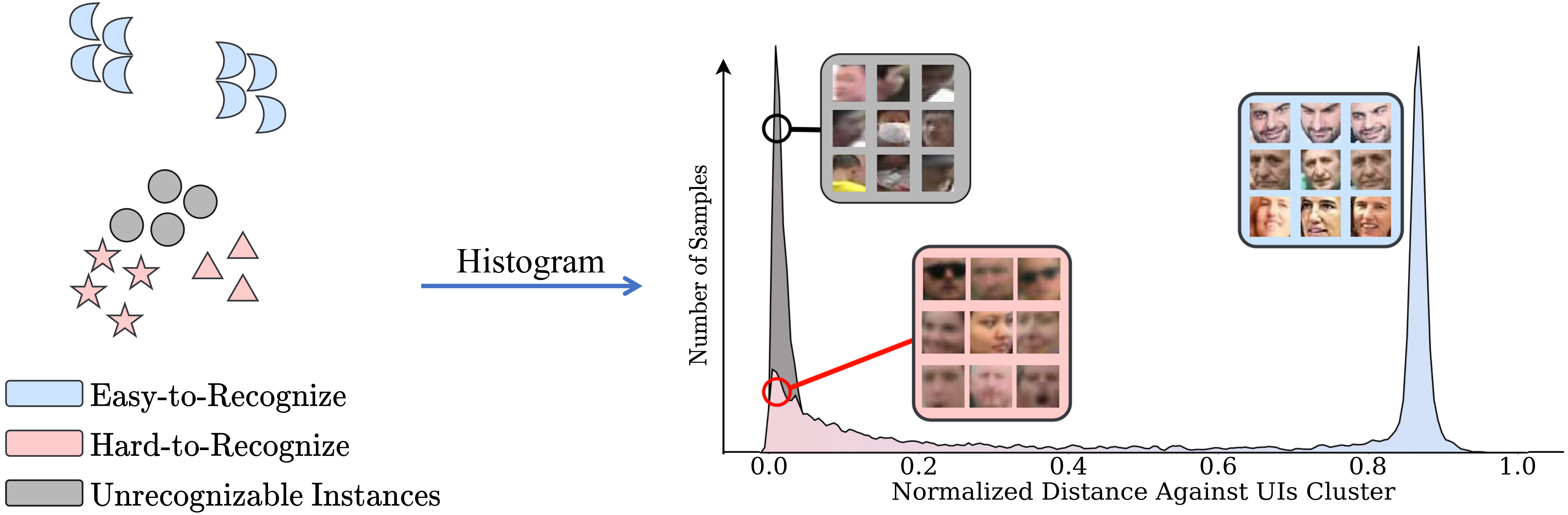
- Range between 16×16 to 32×32 pixels (Zou and Yuen 2011) [60].



- Training of a VLRFR model often suffers from limited meaningful identity-specific patterns.
- Further escalated due to ambiguous inter-class variations with perceptually similar identities.
- Same low-resolution and cross resolution matching.



Motivation

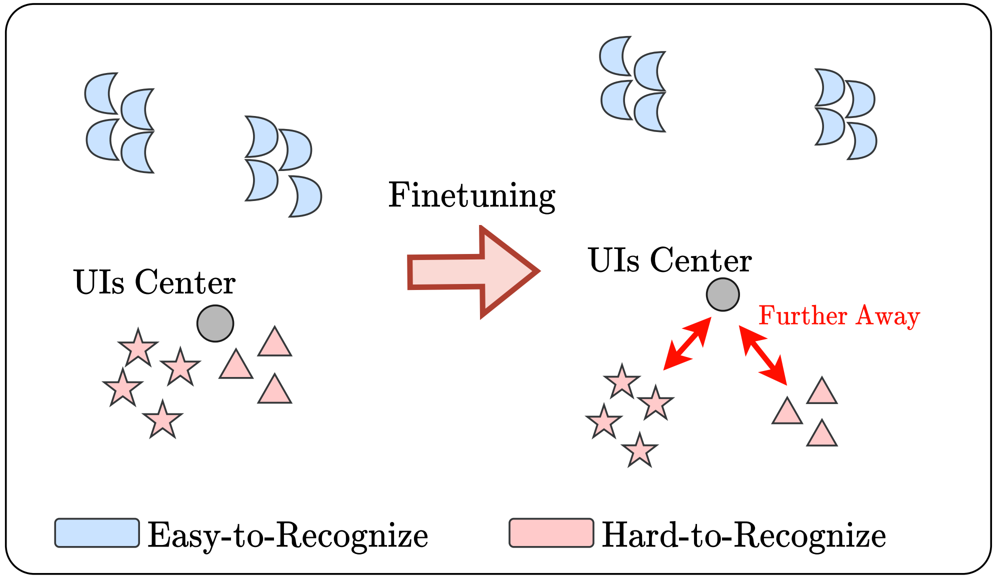


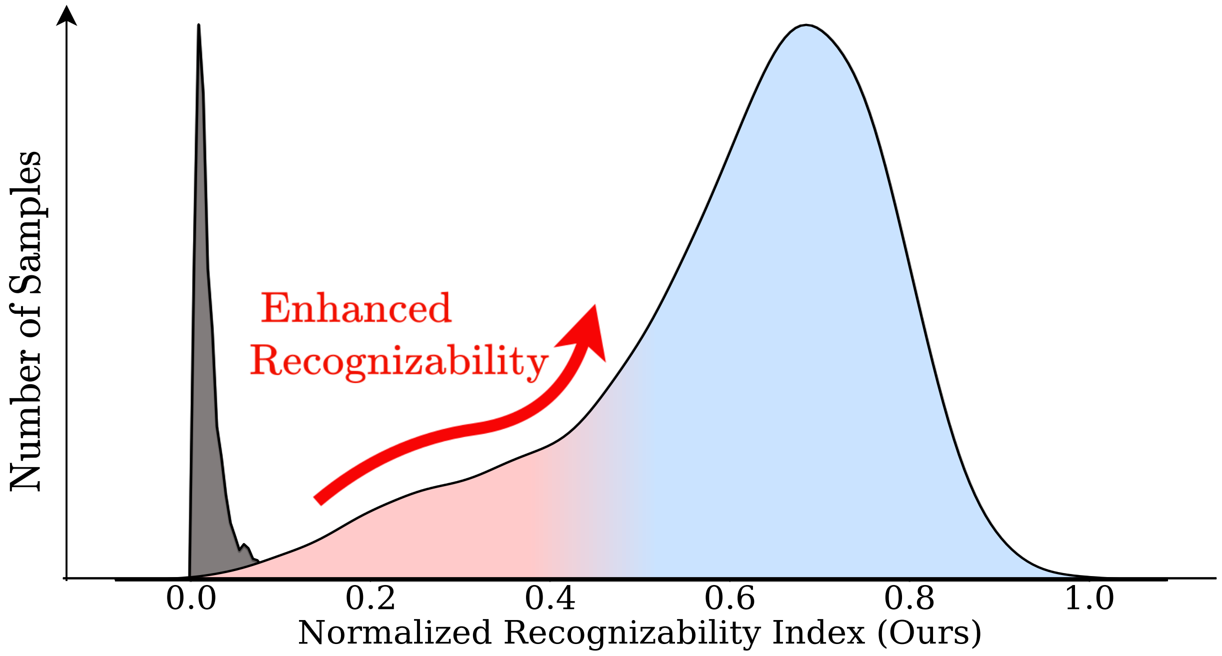
- A deep face model pretrained on high-resolution faces introduces a cluster of unrecognizable indentities (UIs) (**grey**) [9] in the embedding space.

- Hard-to-recognize faces (**red**) from VLR dataset lie closely to these UIs, indicating their low recognizability.

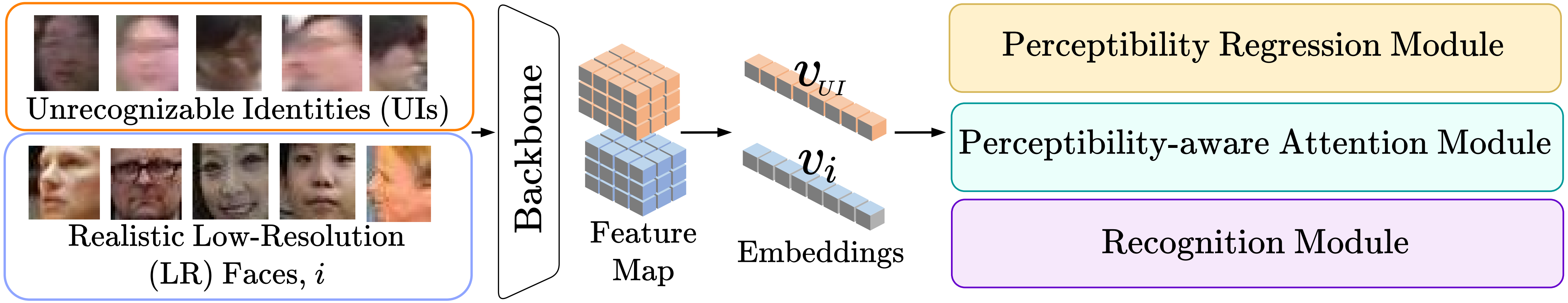
Goals

- Translate face recognizability into a measurable indicator that closely matches human cognition.
- Improve the recognizability of hard-to-recognize instances by pushing them away from the UIs center.





Methodology



- Accepts unrecognizable identities (UIs) and realistic low-resolution face datasets as inputs.

- Comprises 3 main modules.

Perceptibility Regression Module (PRM)

- Learns the recognizability index (RI) and predicts the quality for any face samples including the unseen ones.

Recognizability Index (RI), ξ

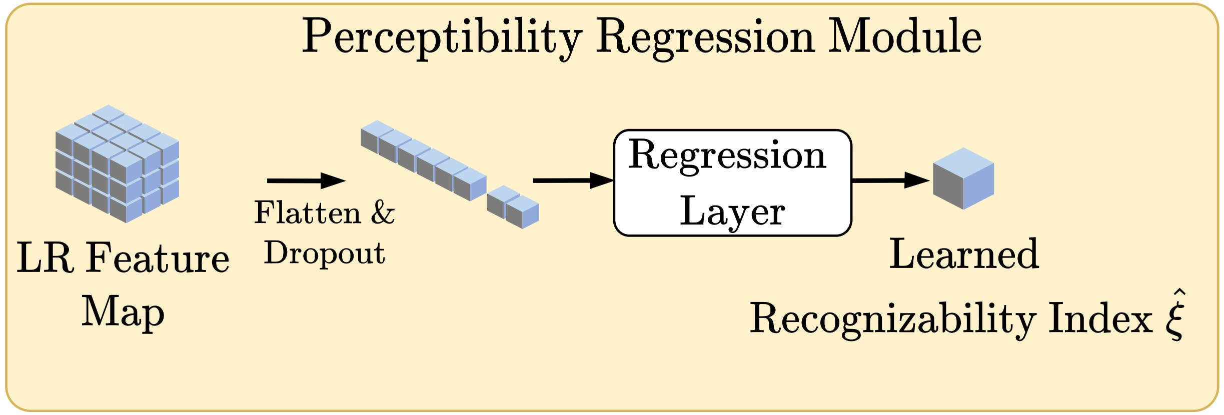
$$\xi_i = d_i^{UI} \frac{d_i^N}{d_i^P + \epsilon}$$

where d_i^P, d_i^N are intra-class, inter-class proximity of L2-normalized face embedding, v_i with respect to its positive prototype and nearest negative prototype.

d_i^{UI} is the cosine distance between v_i and average across normalized UIs embedding.

$$L_{L1} = \begin{cases} 0.5(\xi_i - \widehat{\xi}_i)^2/\beta & \text{if } |\xi_i - \widehat{\xi}_i| < \beta \\ |\xi_i - \widehat{\xi}_i| - 0.5 \times \beta & \text{otherwise} \end{cases}$$

Smooth L1 Loss



Index Diversion Loss

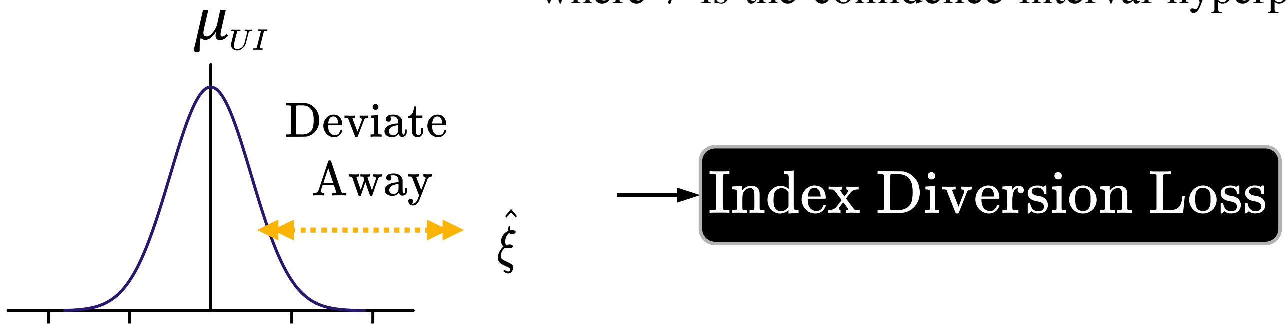
- To enhance the hard-to-recognize instances' recognizability based on learned RI with respect to the UIs.
- The **diversion** of the learned RI of each face in Z-score is defined as:

$$div = \frac{\widehat{\xi_i} - \mu_{UI}}{\sigma_{UI}}$$

where μ_{UI} and σ_{UI} denotes the mean and standard deviation recognizability index of UIs.

- The index diversion loss is then defined as: $L_{ID} = \max(0, \tau - div)$

where τ is the confidence interval hyperparameter.



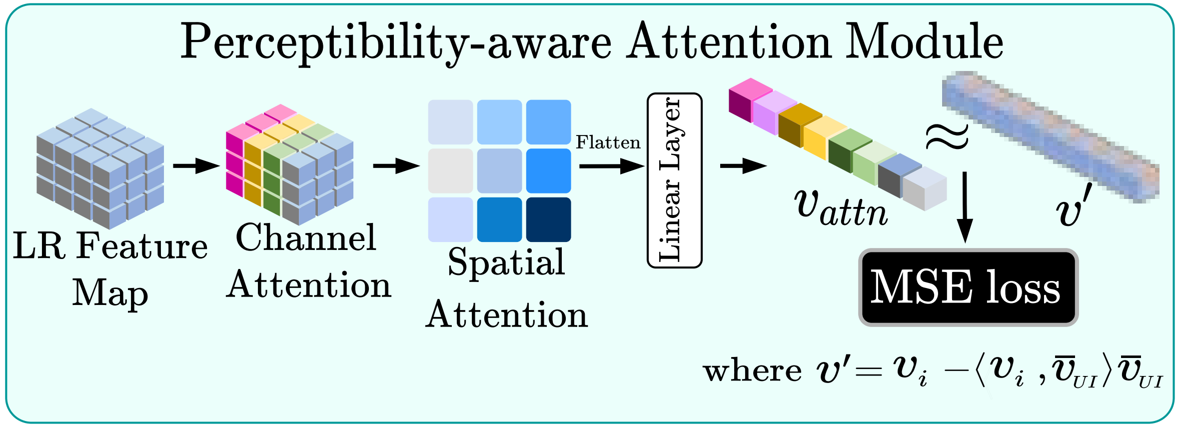
Perceptibility-aware Attention Module (PAM)

- Embedding projection away from UIs cluster center is beneficial for model to highlight meaningful features when face is obscure.

$$\boldsymbol{v}_i' = \boldsymbol{v}_i - \langle \boldsymbol{v}_i, \overline{\boldsymbol{v}}_{UI} \rangle \overline{\boldsymbol{v}}_{UI}$$

$\overline{\boldsymbol{v}}_{UI}$ is L2-normalized average of UIs' embedding.

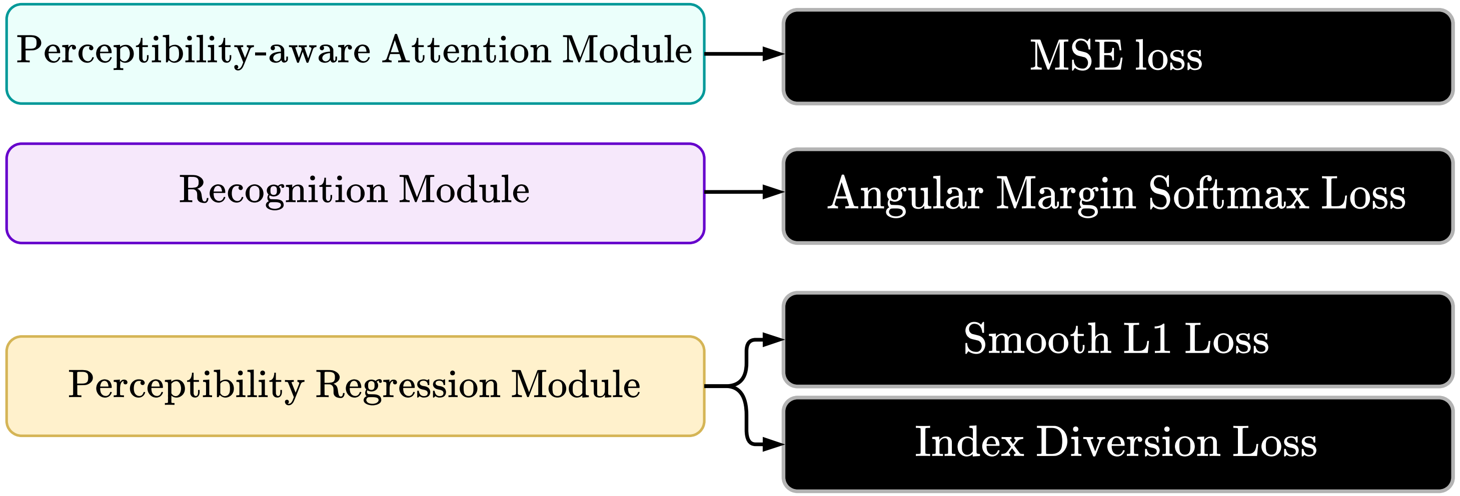
- Approximating $\boldsymbol{v}_i'$ through PAM module using MSE loss as follows:



- The projection of embedding away from UIs cluster can be deemed as RI-enhanced embedding.
- The projection guides the model to attend to parts of embedding that **represent the salient facial features for recognizability**.

Loss Computation

- For recognition module, the angular margin SoftMax loss (i.e. ArcFace) is chosen.



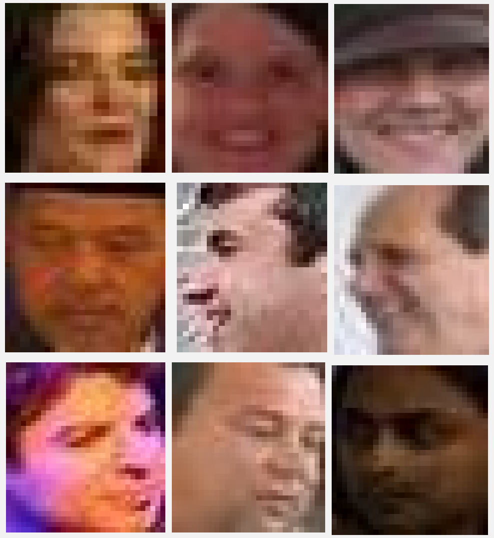
- The total loss computation is written as:

$$L_{total} = L_{cls} + \alpha L_{L1} + \beta L_{ID} + \gamma L_{MSE}$$

where α, β, γ are the respective weighting factors for each loss.

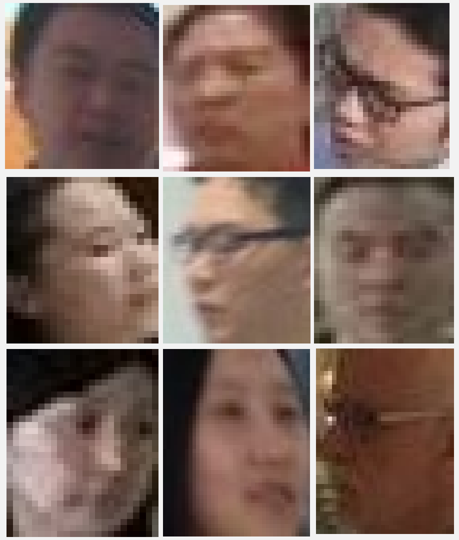
Experiments

Very Low-Resolution Face Recognition Datasets:



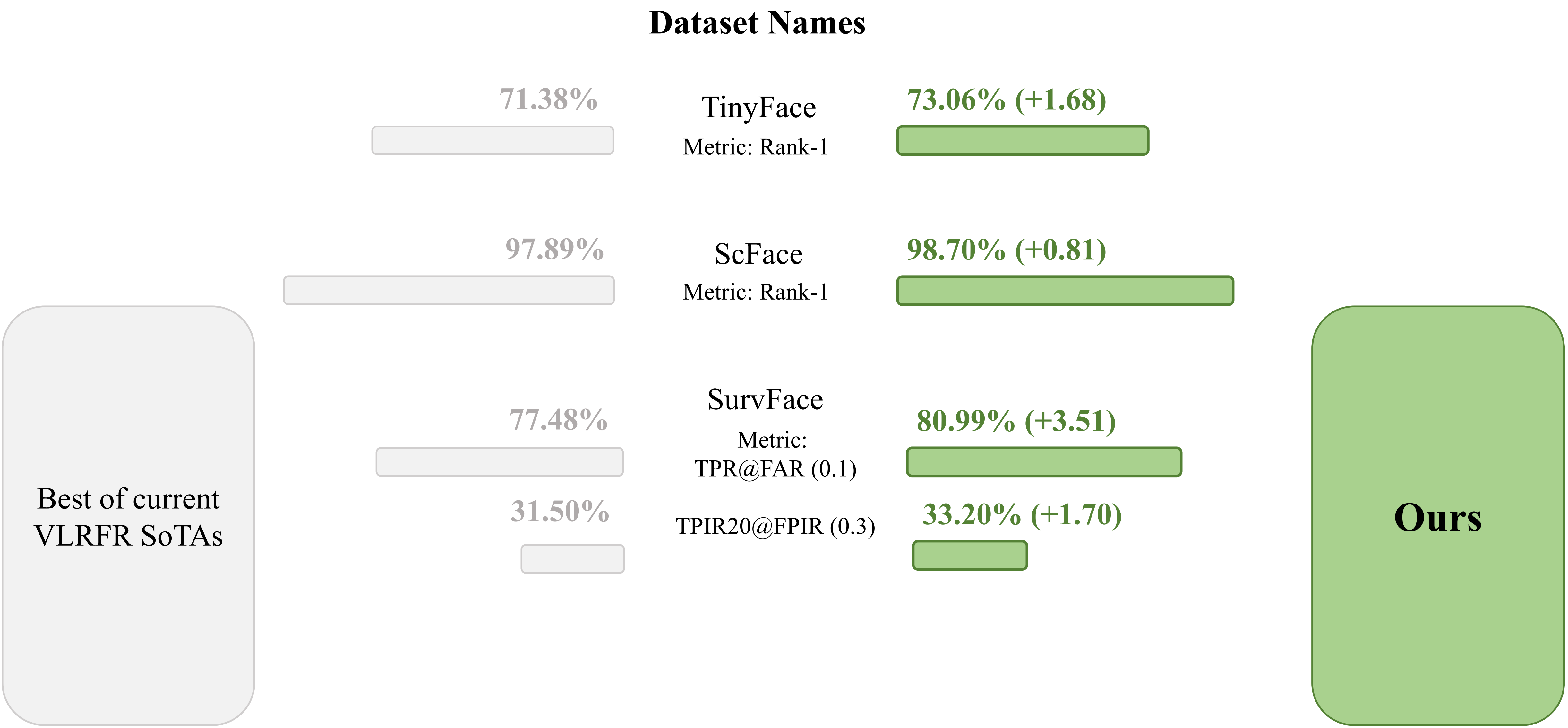
TinyFace

ScFace



SurvFace

Performances in 3 VLR Datasets



Ablation Analysis

Method	$\mathcal{L}_{cls}$	$\mathcal{L}_{ID}$	$\mathcal{L}_{MSE}$	$\mathcal{L}_{L1}$	Rank-1 IR (%)
Cross Entropy (2014)	✓				68.884
NormFace (2017)	✓				68.026
CosFace (2018)	✓				70.306
MV-Softmax (2020)	✓				70.547
CurricularFace (2020b)	✓				70.655
MagFace (2021)	✓				70.467
AdaFace (2022)	✓				70.359
Baseline (ArcFace) (2019)	✓				70.333
I	✓	✓			71.298
II	✓		✓		71.540
III	✓			✓	71.674
Ours	✓	✓	✓	✓	**71.915**

Direct elevation of recognizability

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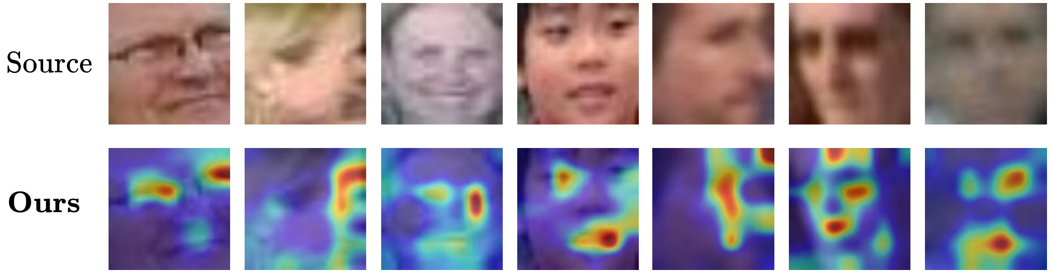
Attention on embedding projection away from UIs cluster allows the model to highlight salient regions within a face.



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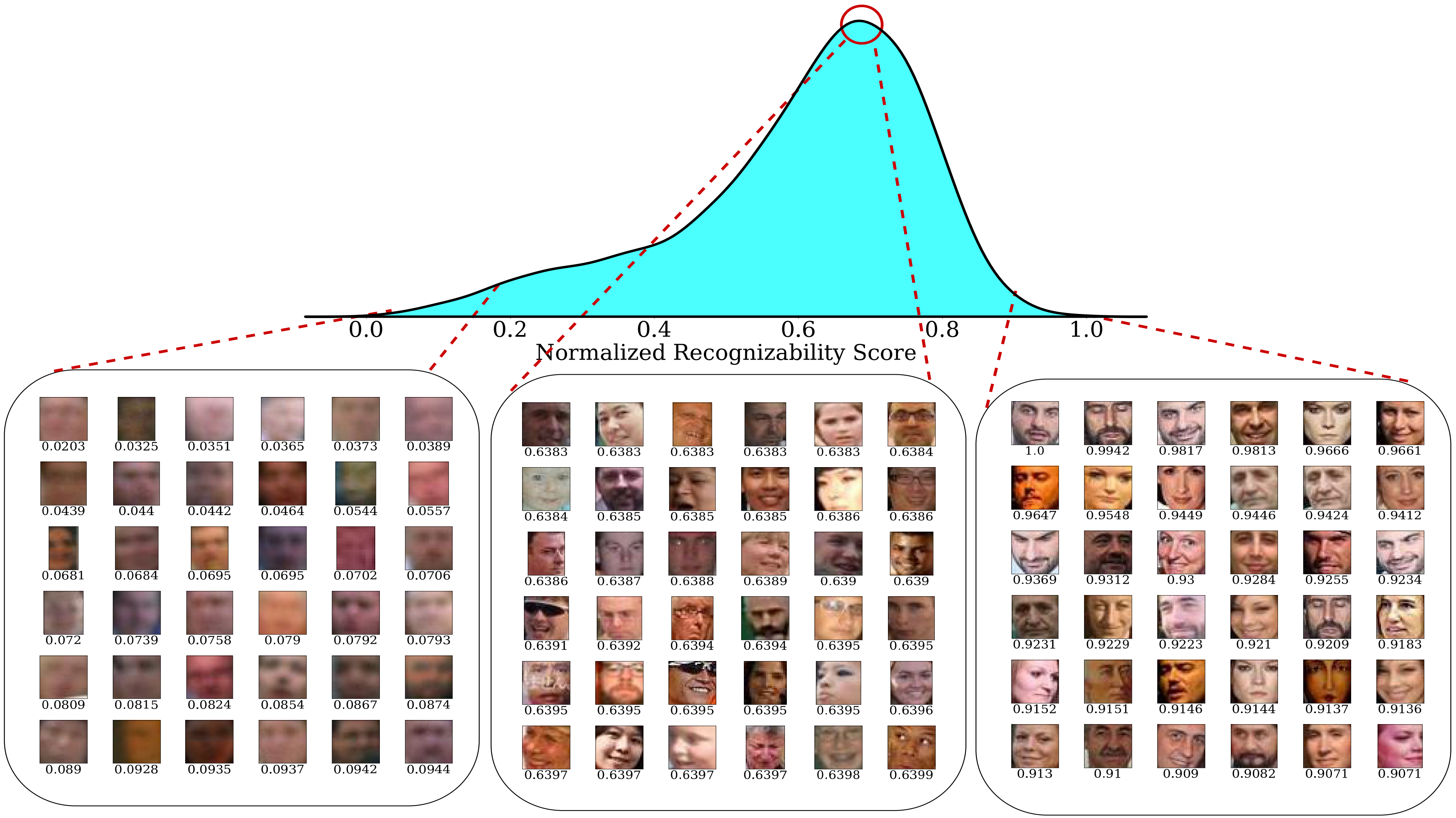
Simultaneously benefit from recognizability-aware embedding learning, which RI can be viewed as model's confidence corresponding to classifiability.

Recognizability Index

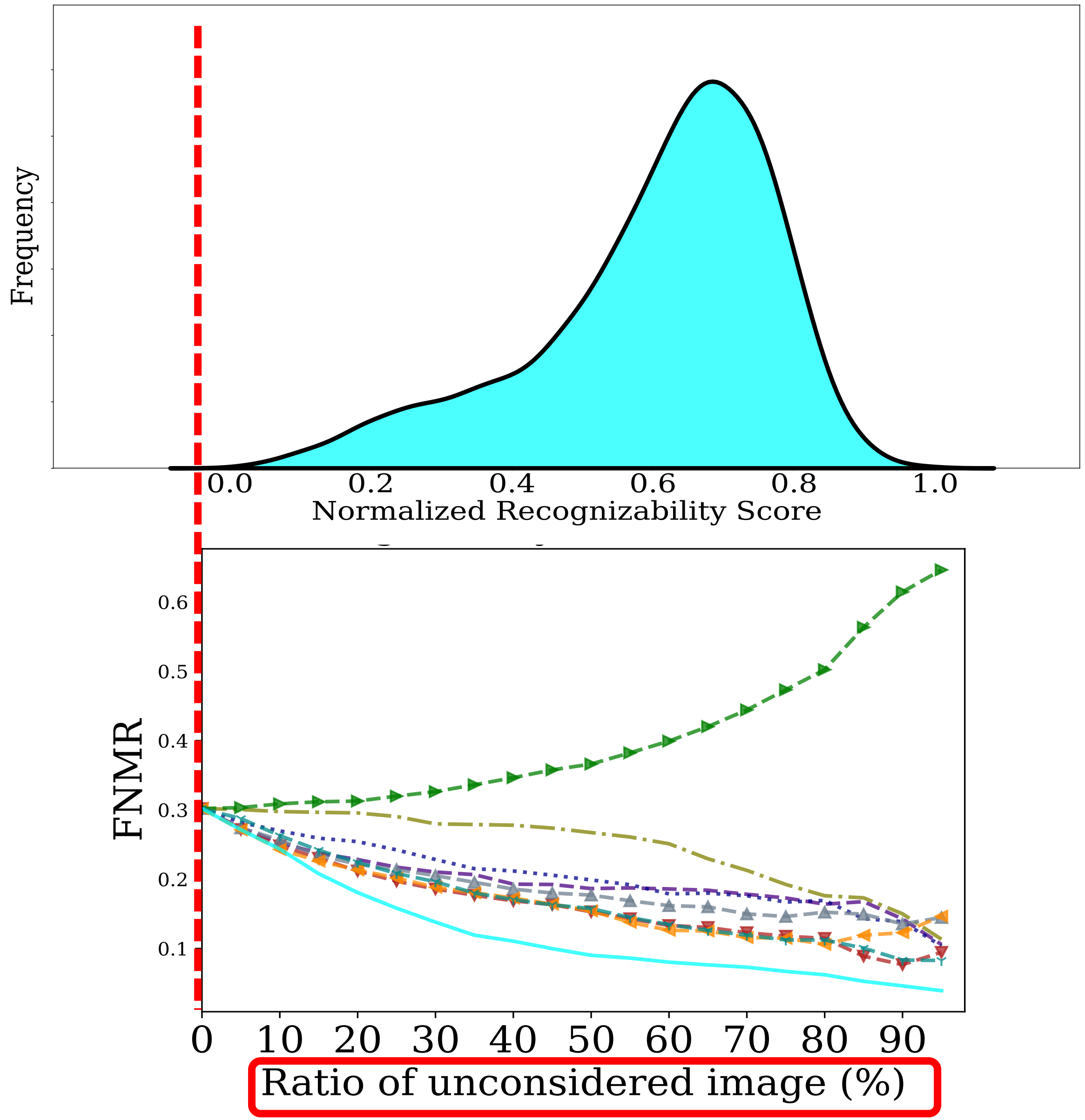
- Recognizability distribution of each face instance from TinyFace testing set is shown as follows:



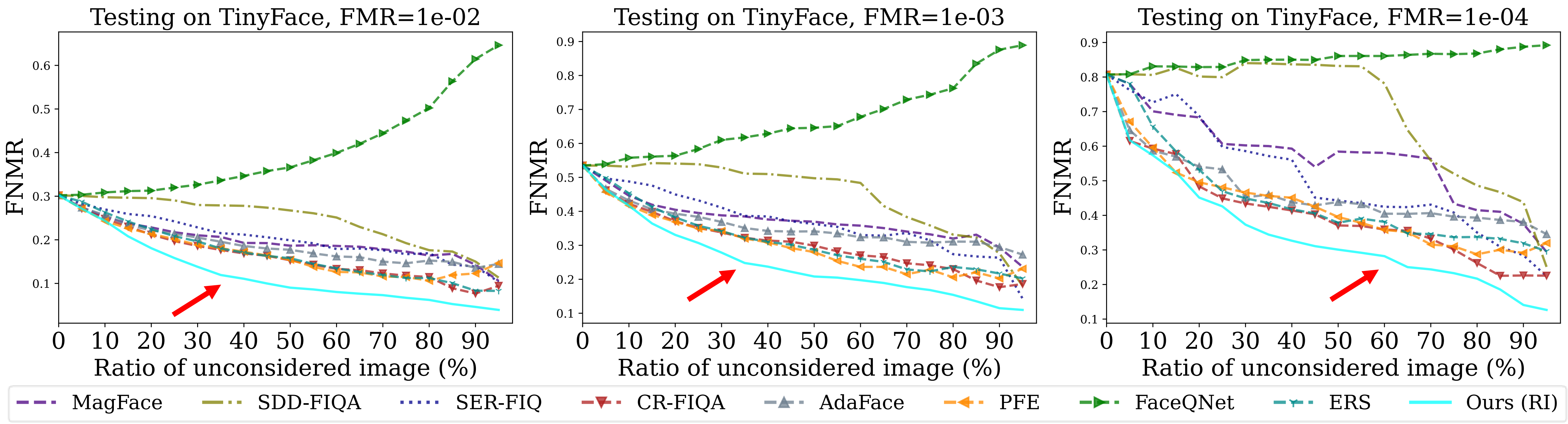
Error vs. Reject Curve (ERC)

- Generated upon verification + **ratio of unconsidered images.**

- The portion of images **to the left of red line in the histogram** will be unconsidered for verification (FNMR @ FMR) task.



Error vs. Reject Curve



- The RI is a reliable metric for assessing recognizability, such that VLR faces that are more recognizable are learned with higher RIs (and vice versa).

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Thank You

Jacky Chen Long Chai[1] Tiong-Sik Ng[1] Cheng-Yaw Low[2] Jaewoo Park[1] Andrew Beng Jin Teoh[1]
[1]{jackyccl, ngtiongsik, julypraise,bjteoh}@yonsei.ac.kr [2]{chengyawlow}@ibs.re.kr

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