

A Deep Adversarial Framework for Visually Explainable Periocular Recognition

João Brito and Hugo Proença

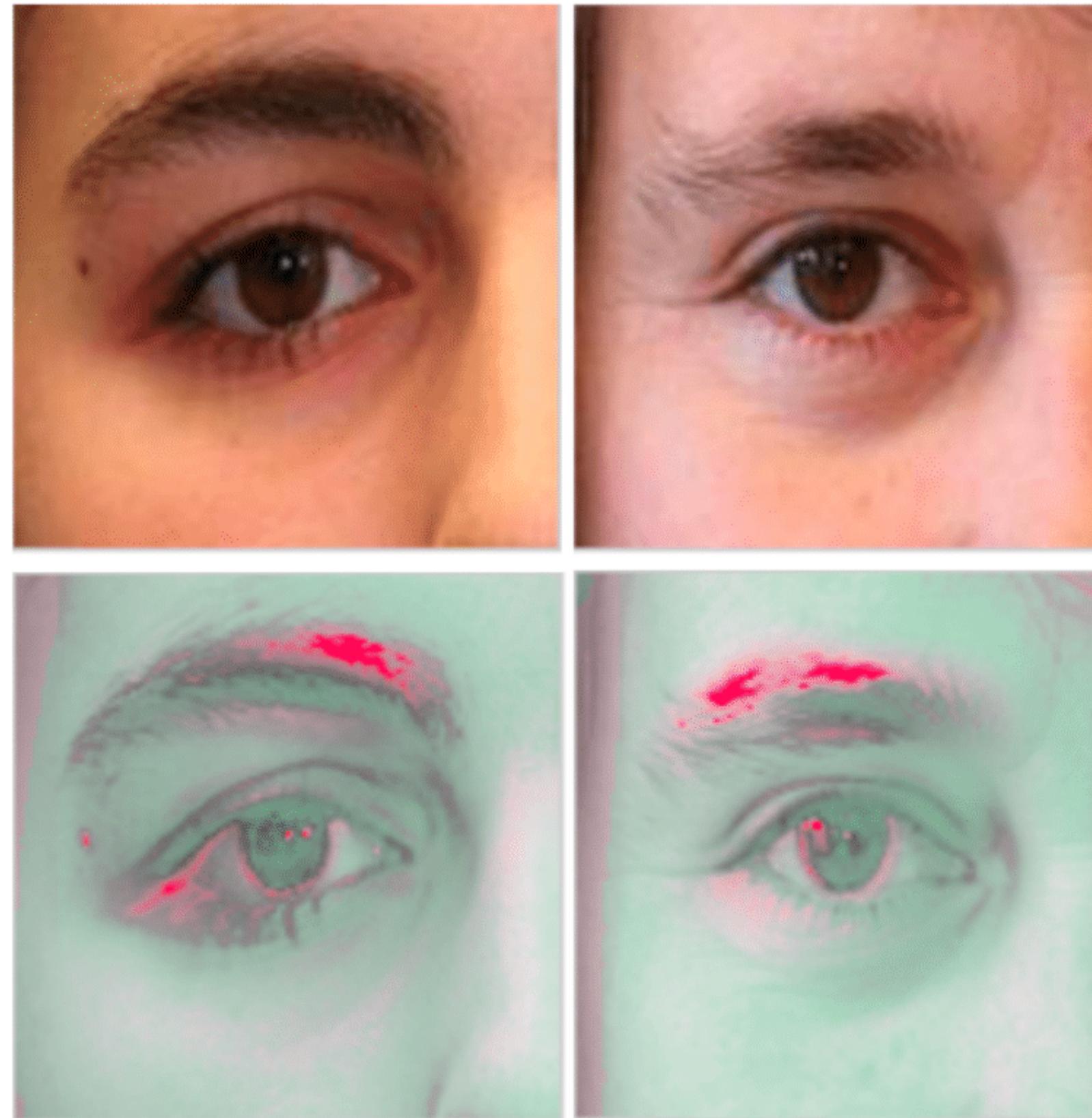
IT: Instituto de Telecomunicações - University of Beira Interior

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Visual Explainability

- ✓ Immediately understandable
- ✓ Context-aware

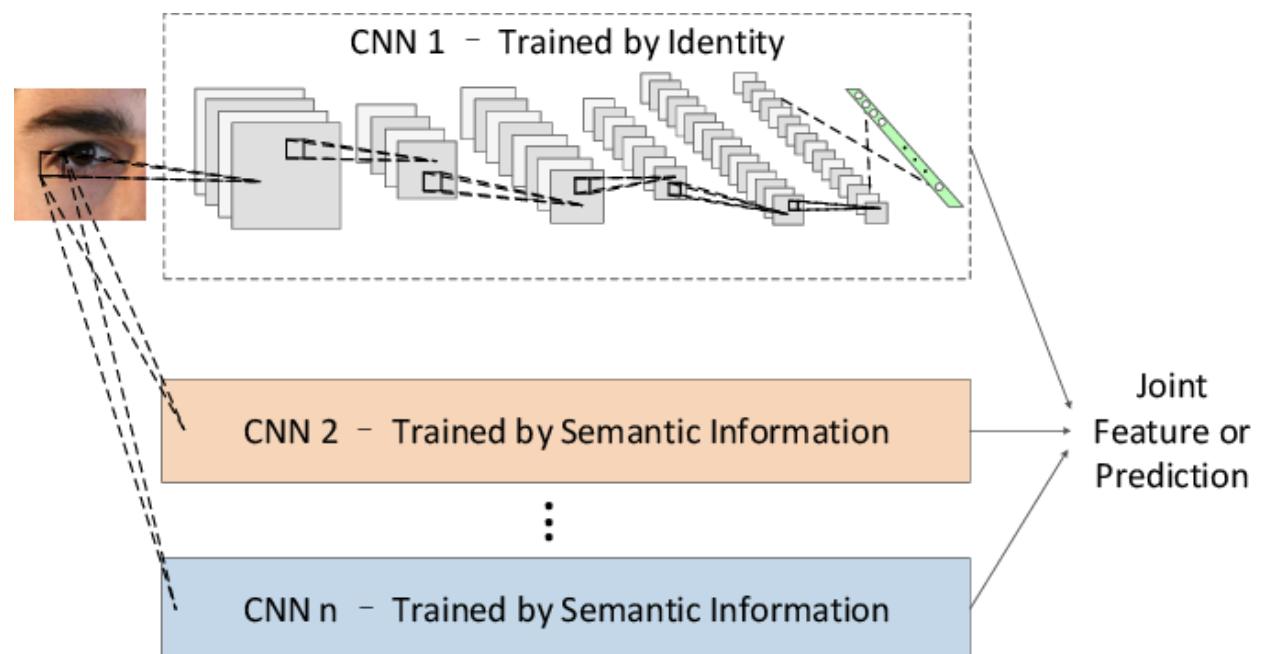
Synthetic images increase data variability, attenuate differences in phase and enable component-by-component matching



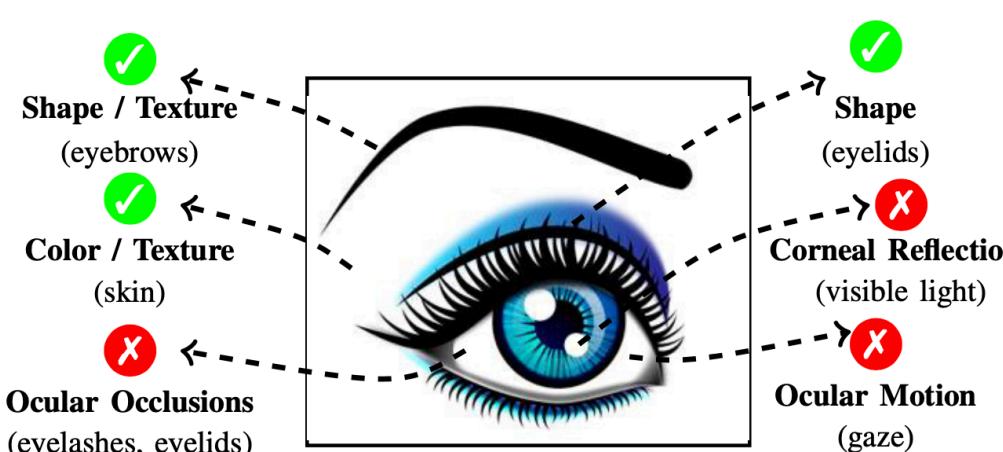
Results attained by the proposed solution.

Related Work

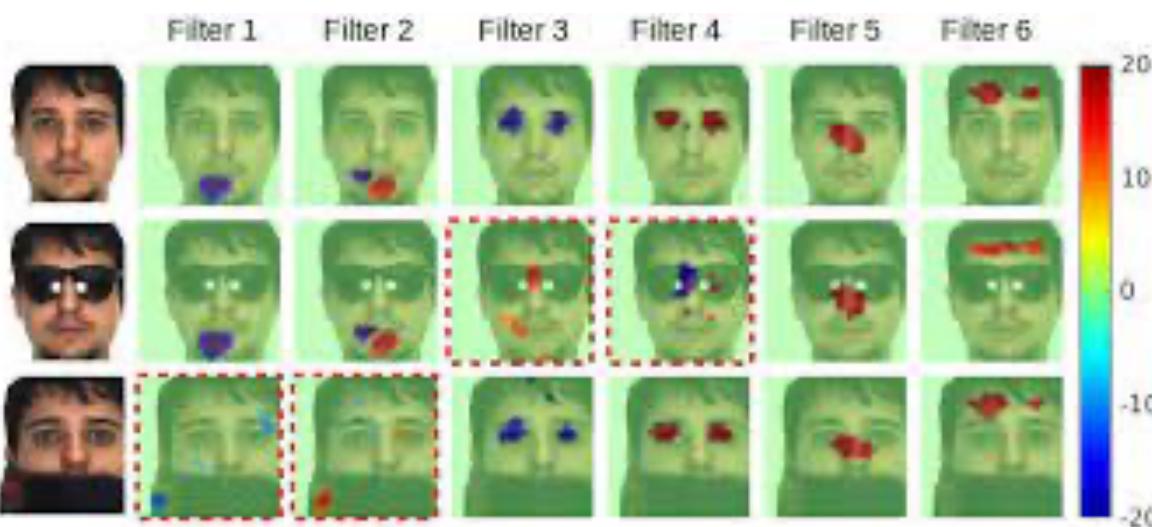
Periocular / Biometric Recognition



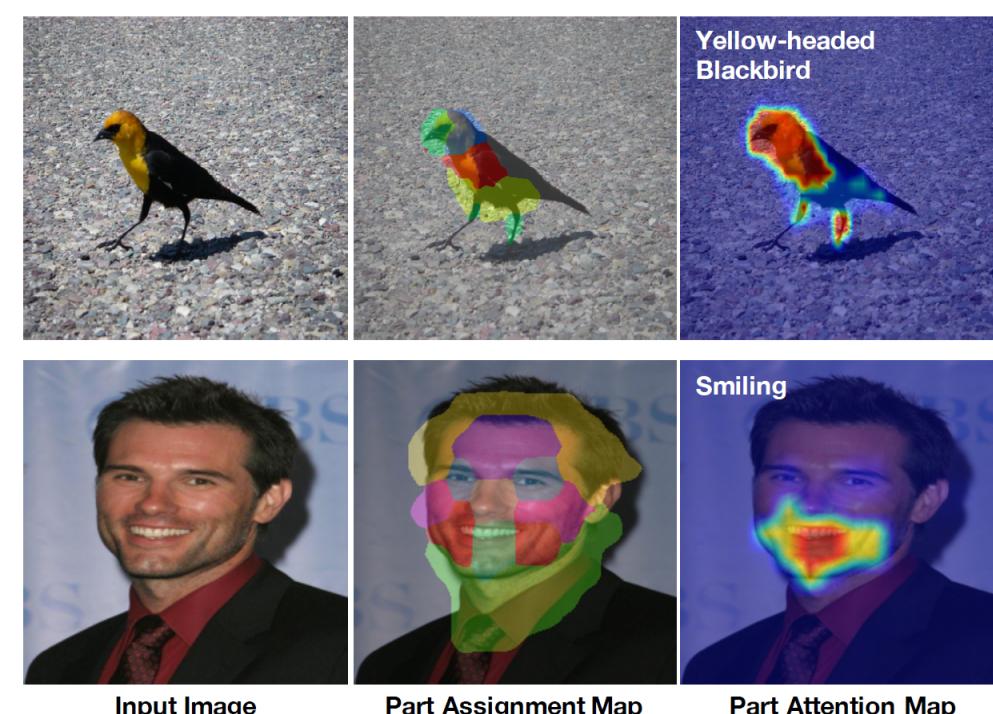
Zhao and Kumar, 2017



Proen  a and Neves, 2018

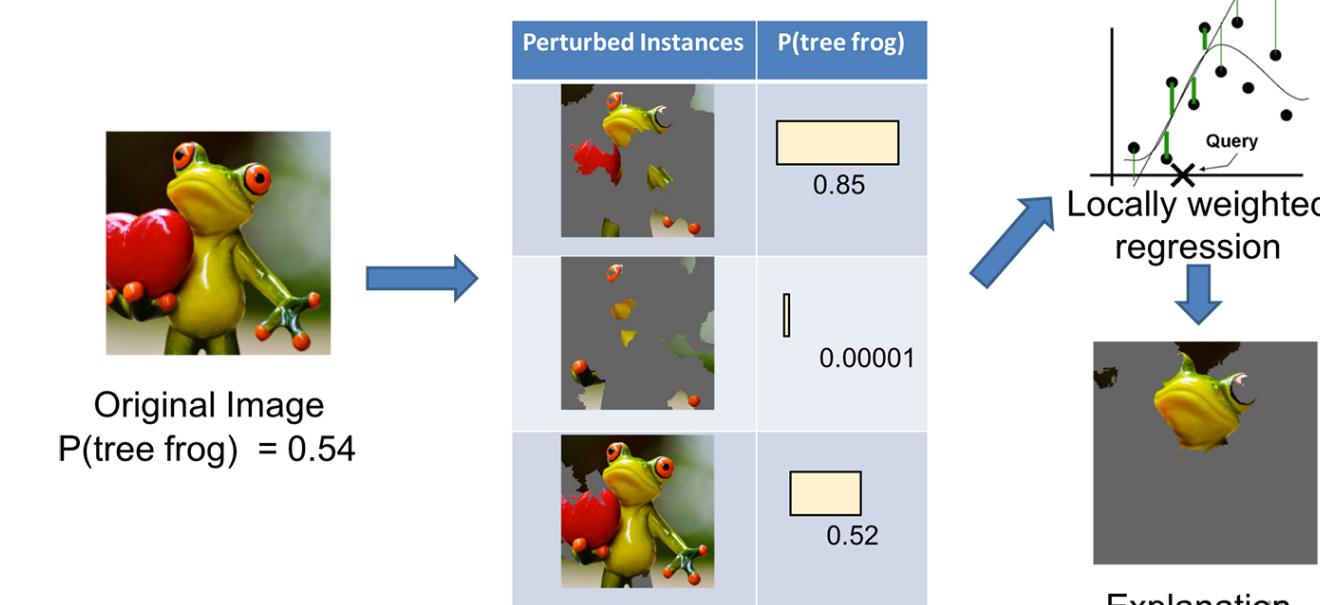


Yin et al., 2019

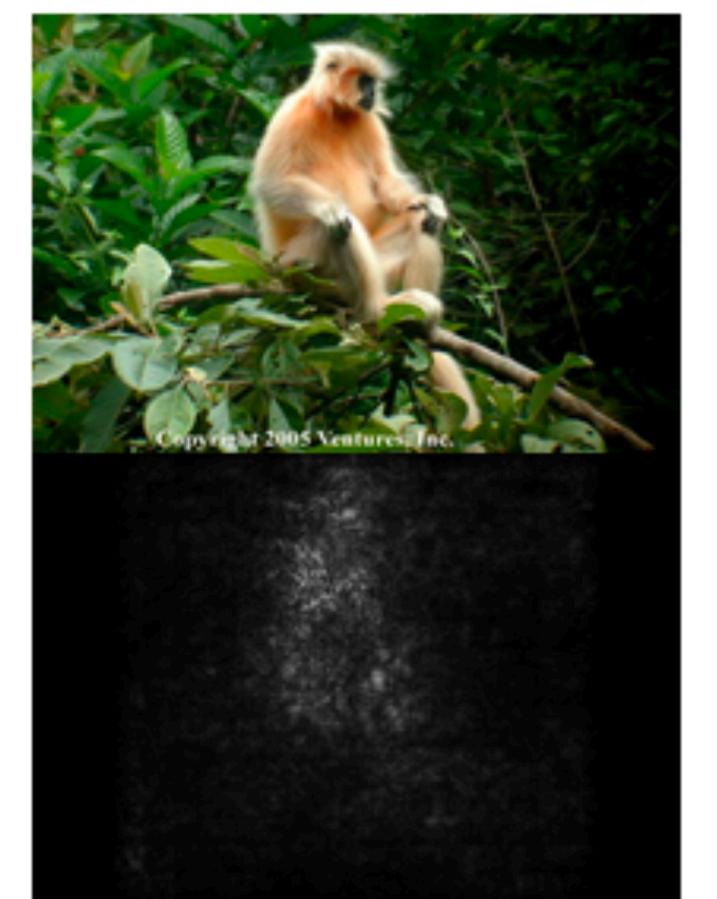


Huang and Li, 2020

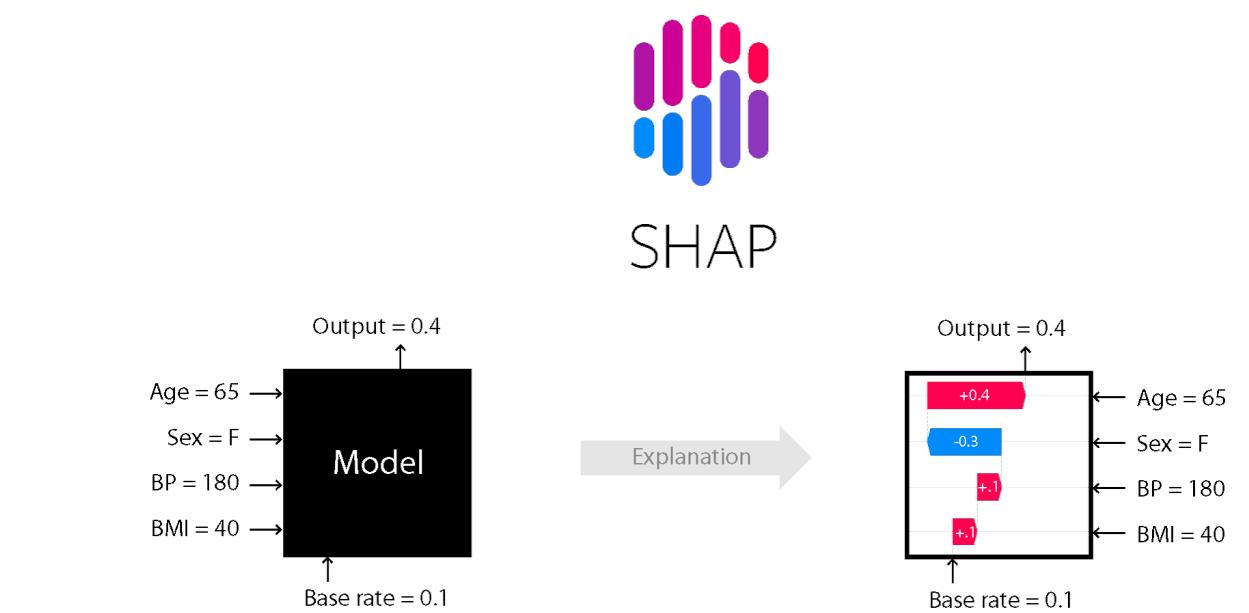
ML Explainability



Ribeiro et al., 2016



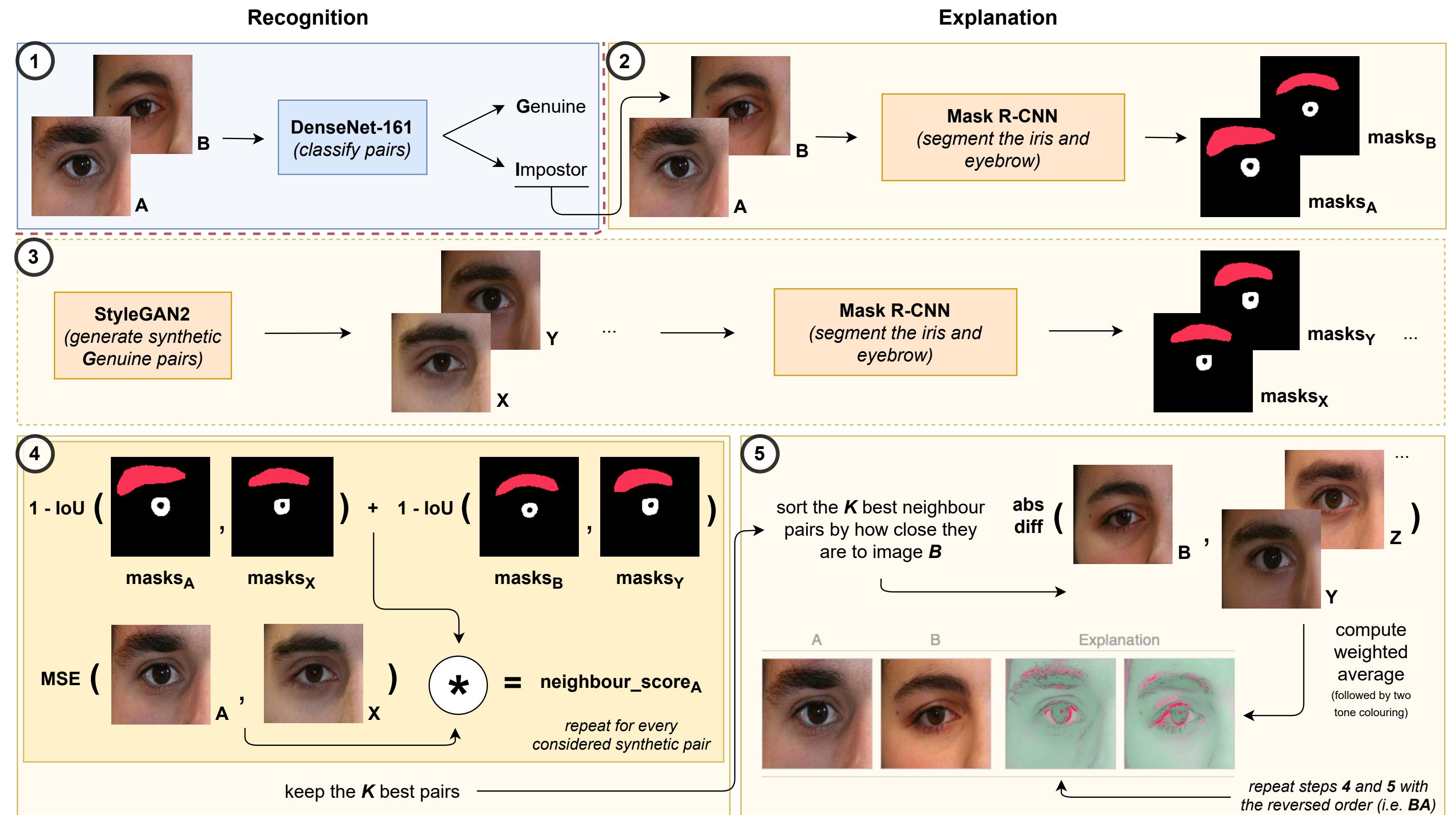
Simonyan et al., 2017



Lundberg and Lee, 2017

Proposed Method

- ✓ **Recognition and Explanation phases**
- ✓ **Modular architecture**
- ✓ Search amongst a **high quality synthetic dataset** of “Genuine” samples, for optimal matches

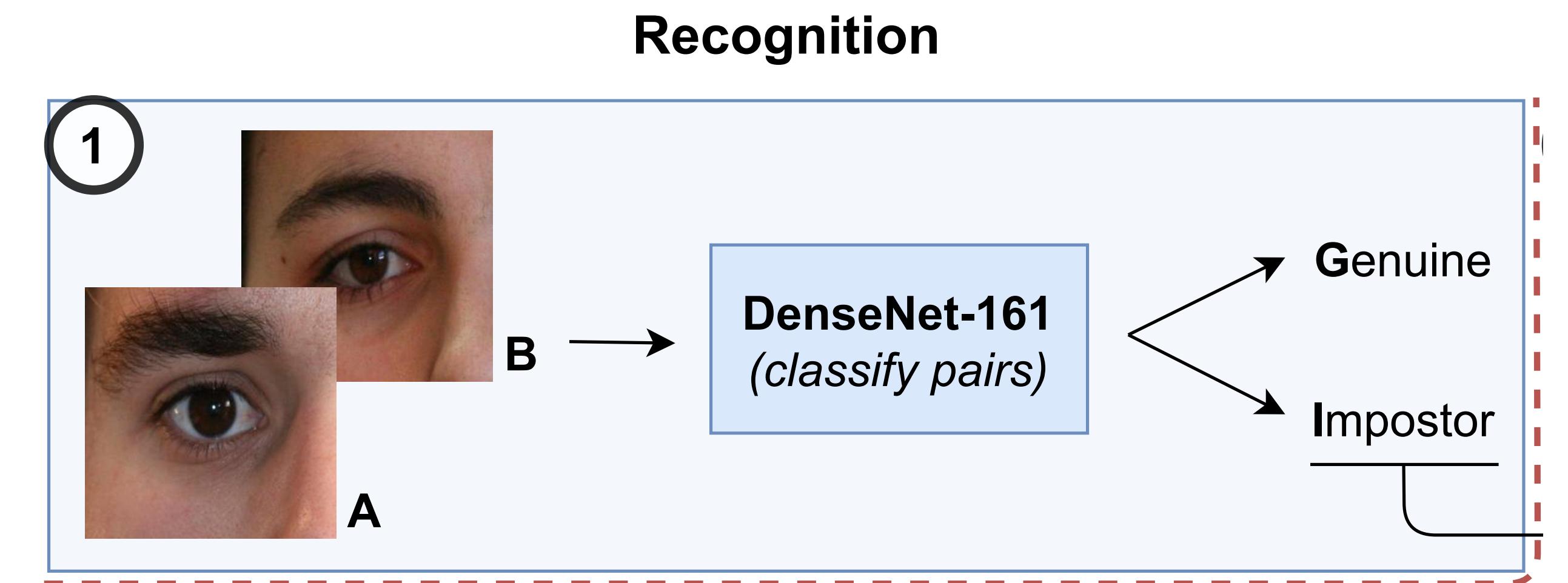


Overview of the proposed method.

Proposed Method

Recognition

- ✓ **Goal:** discriminate between “Genuine” and “Impostor” pairs
- ✓ **CNN** (DenseNet family)
- ✓ **Identity verification** problem



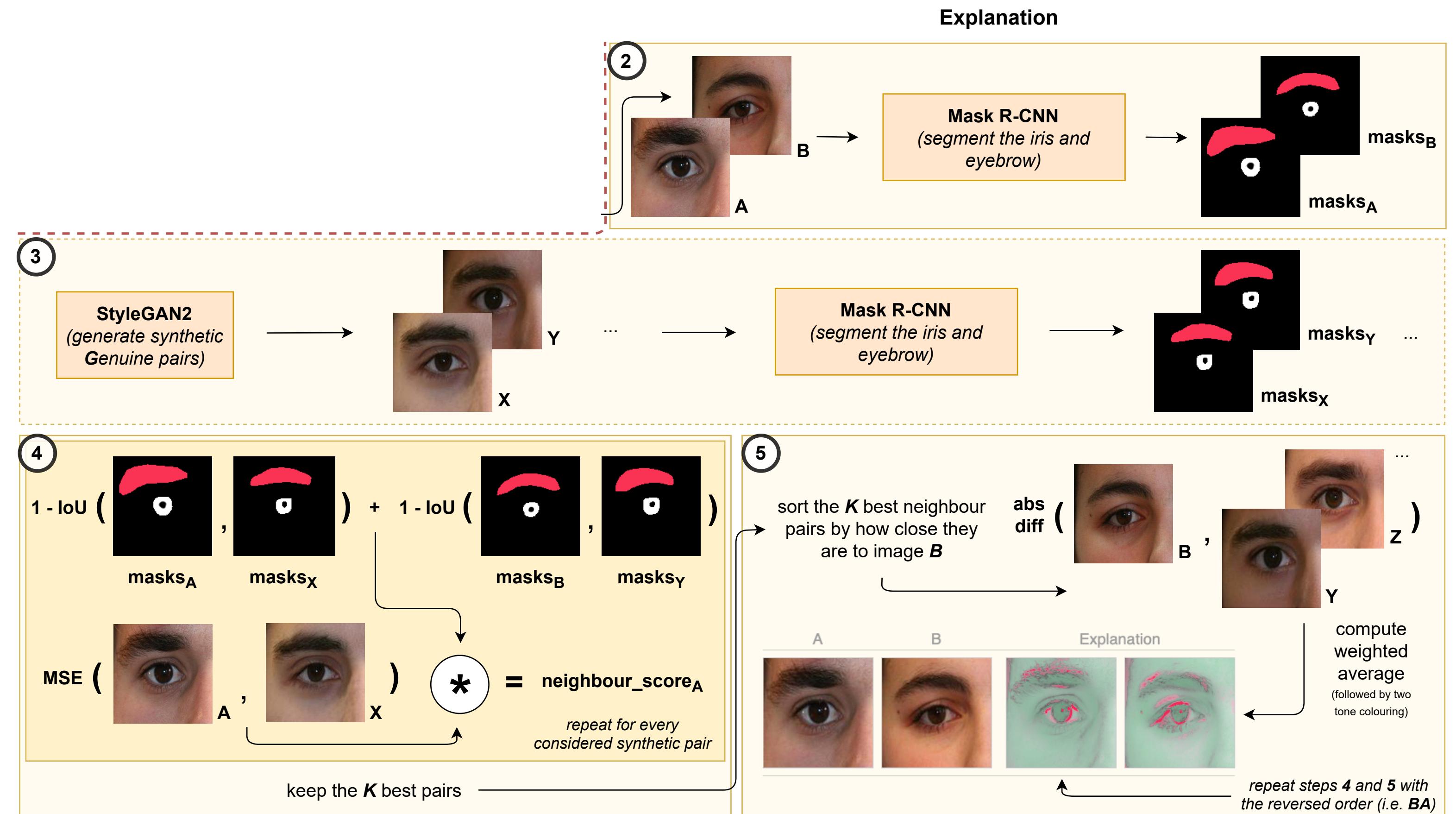
Proposed Method

Explanation

- ✓ **Goal:** produce visually pleasing explanations for the “Impostor” decision
- ✓ **Mask R-CNN** (for component segmentation)
- ✓ **StyleGAN2** (for high quality image synthesis)

“Which synthetic pairs are **closest** to our query?”

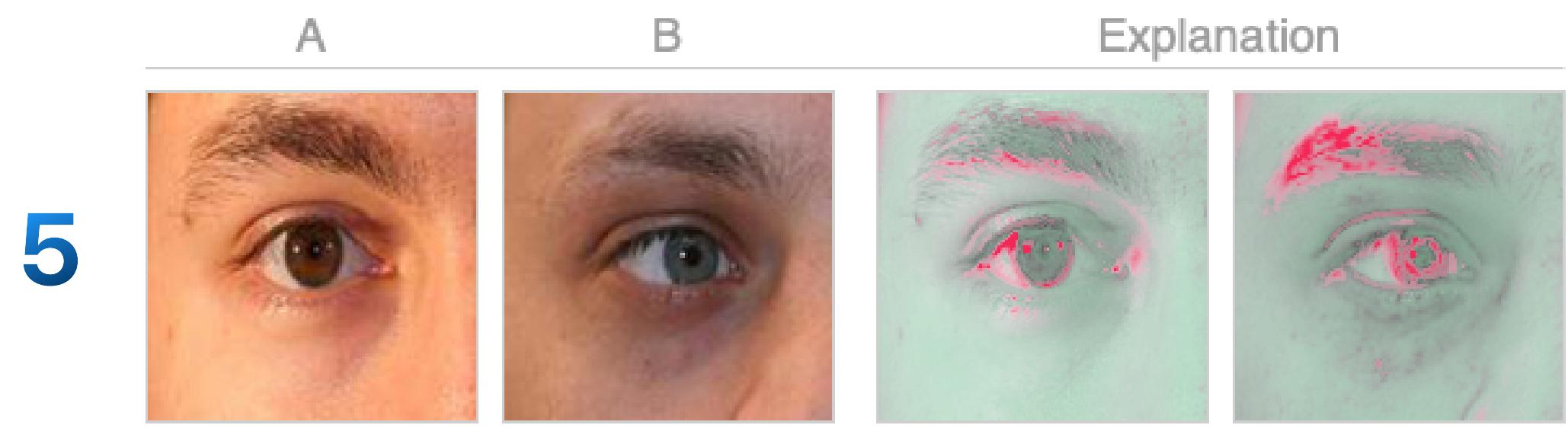
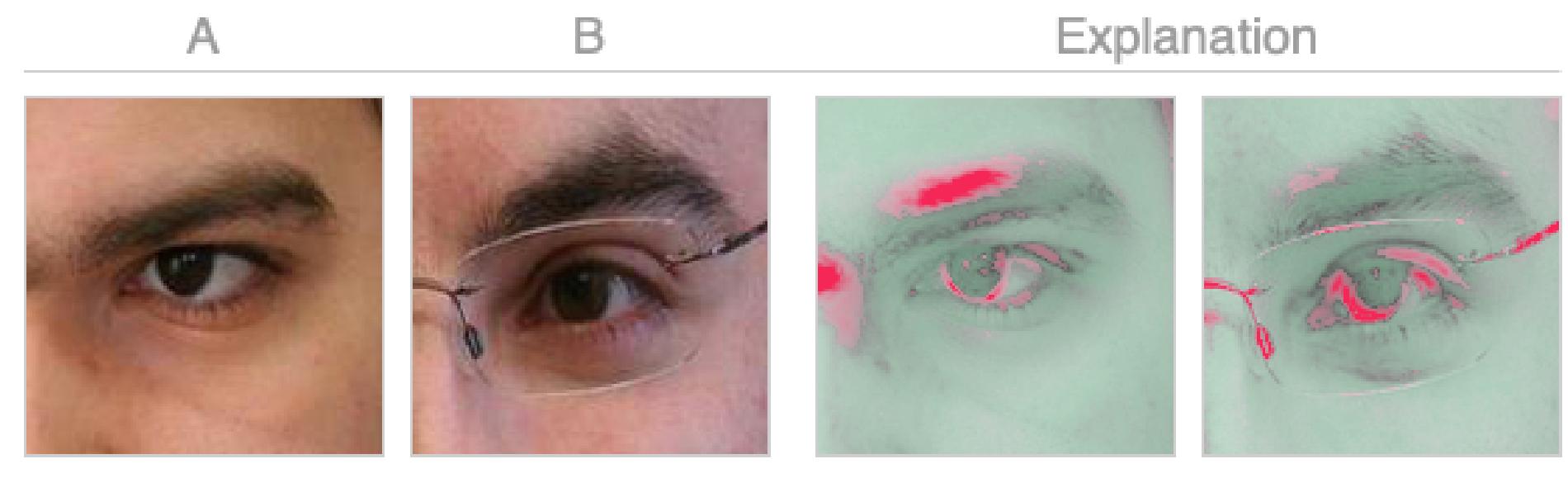
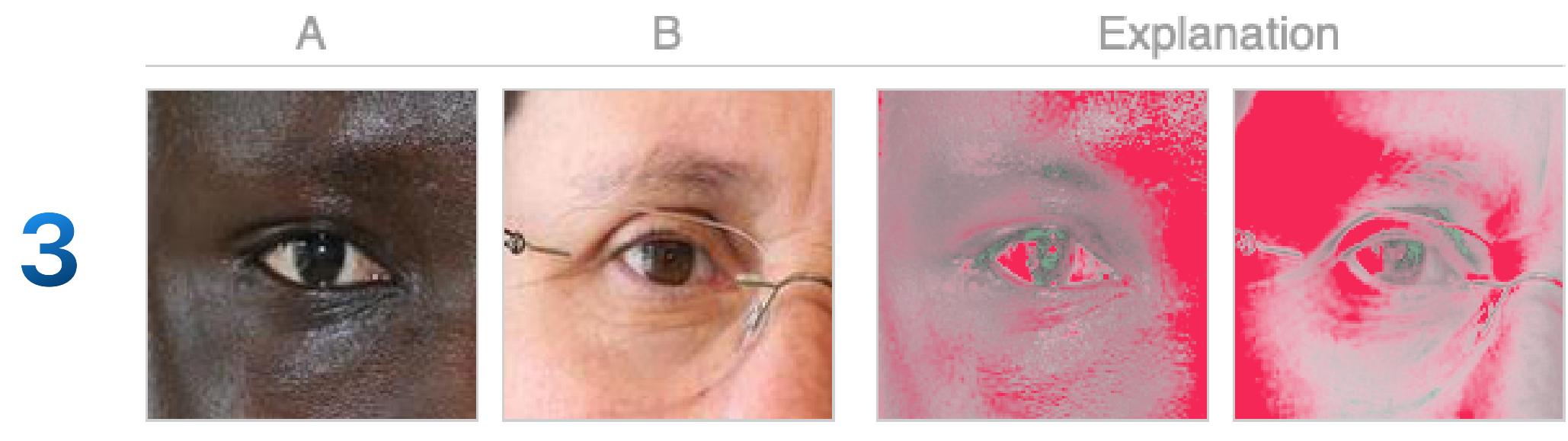
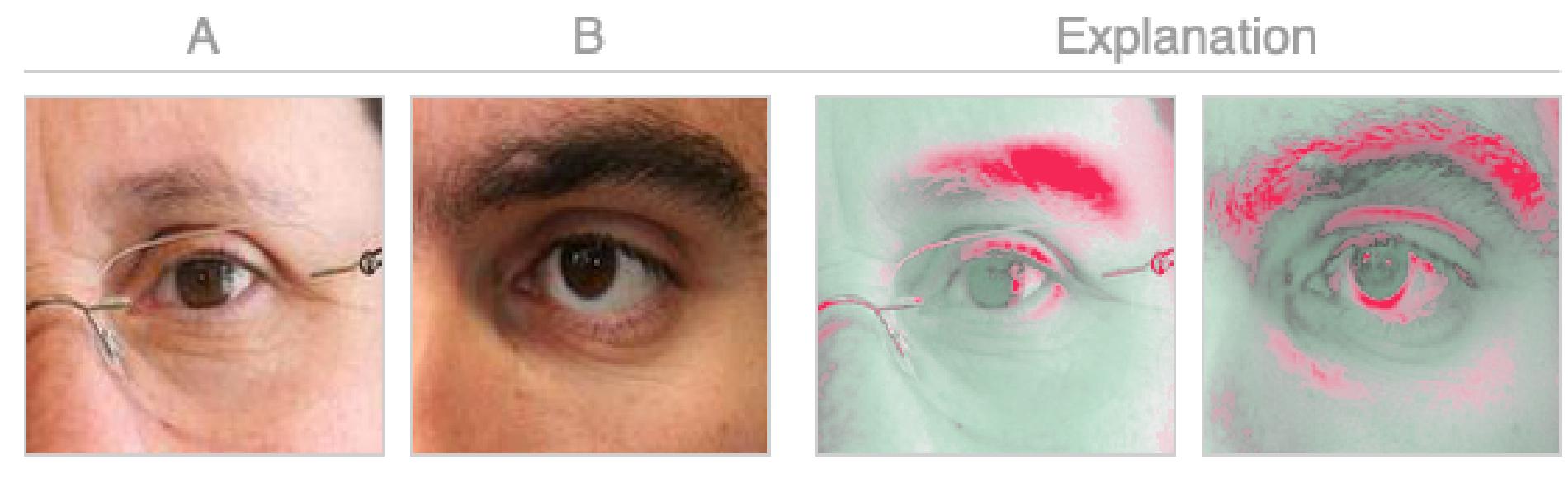
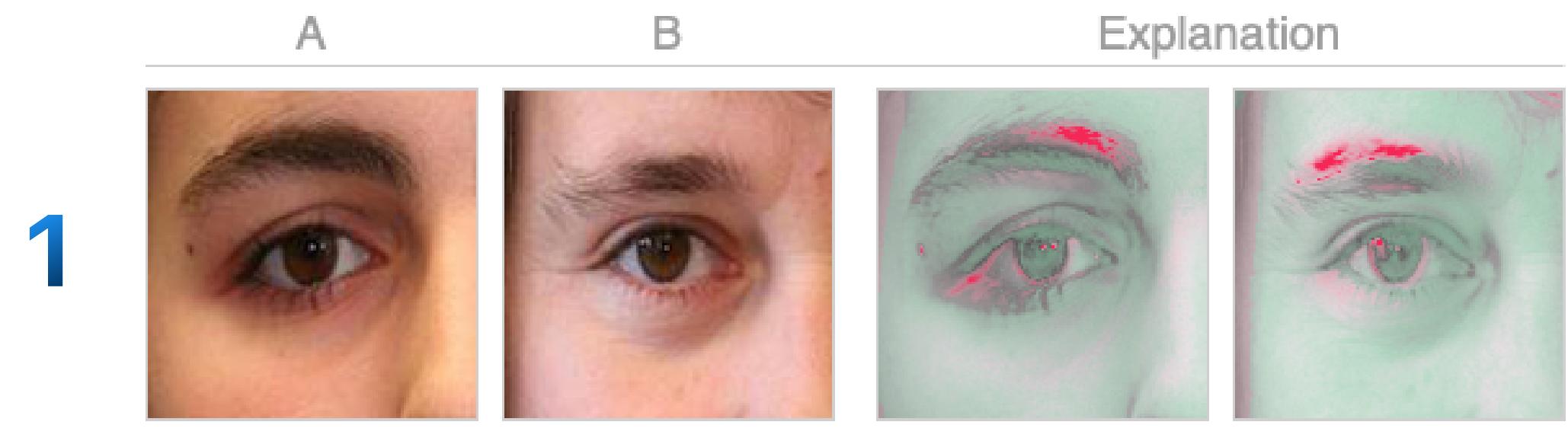
$$s_X = \omega_{\text{masks}} * \|\text{query_pair}_A - \text{neighbour}_X\|_2, \quad (1)$$



Explanation component of our framework.

Qualitative Results

- Regions that contribute to the "Impostor" class
- Regions that do not contribute to the "Impostor" class



Readable and explainable results attained by our method.

Recognition Results

- ✓ **Bootstrapping-like strategy**
(90% of the UBIRIS.v2 dataset
→ 80% training + 20% test)
- ✓ **10 repetitions**
- ✓ Both world settings
- ✓ **Competitive** performance w.r.t.
the state-of-the-art

Method	EER	AUC
Ours (open-world)	$0.108 \pm 3e-2$	$0.813 \pm 5e-2$
Ours (closed-world)	$0.087 \pm 2e-2$	$0.910 \pm 2e-2$
Zhao and Kumar [23]	$0.109 \pm 2e-3$	—

Comparison between our framework and a state-of-the-art method on the UBIRIS.v2 dataset.

[23] Z. Zhao and A. Kumar. Accurate periocular recognition under less constrained environment using semantics-assisted convolutional neural network. *IEEE Transactions on Information Forensics and Security*, 12(5):1017–1030, 2017.

Conclusions and Further Work

- ✓ An integrated framework capable of delivering explainable justifications
- ✓ Modularity allows for other recognition capabilities without compromising the explanations
- ✓ Applicability to other domains (e.g., facial recognition and subsequent explanation)
- ? Better structuring of the synthetic dataset (i.e., based on attributes), allowing for improved / faster search

Questions?

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<https://github.com/ojoaobrito/ExplainablePR>

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