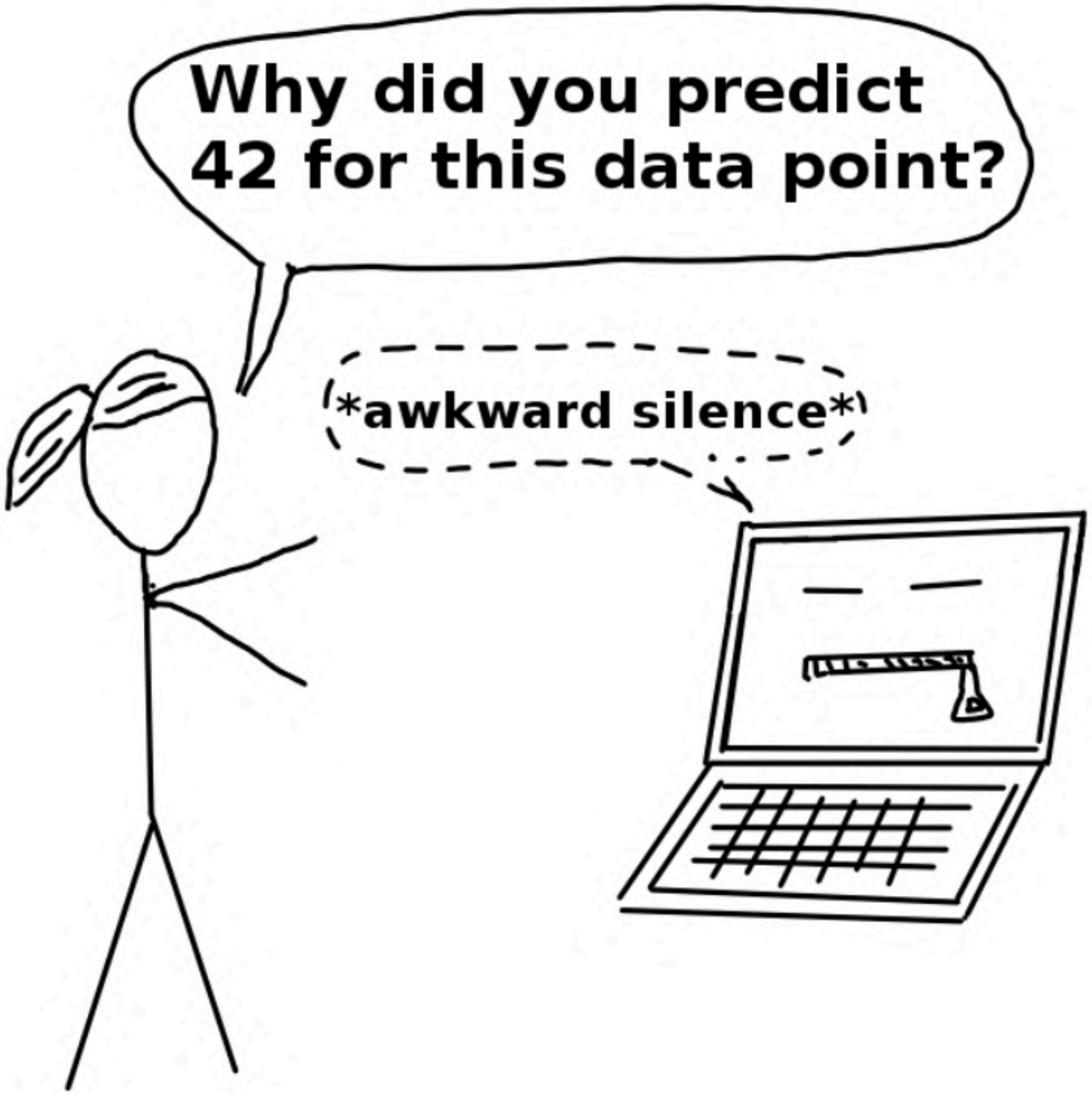
JOÃO BRITO | PROF. DR. HUGO PROENÇA | JANUARY 2021

Deep Adversarial Frameworks for Visually Interpretable Periocular Recognition



[1]

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Problem Description

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Given two images from the **periocular region**, determine whether they came from the **same subject** and **explain** why

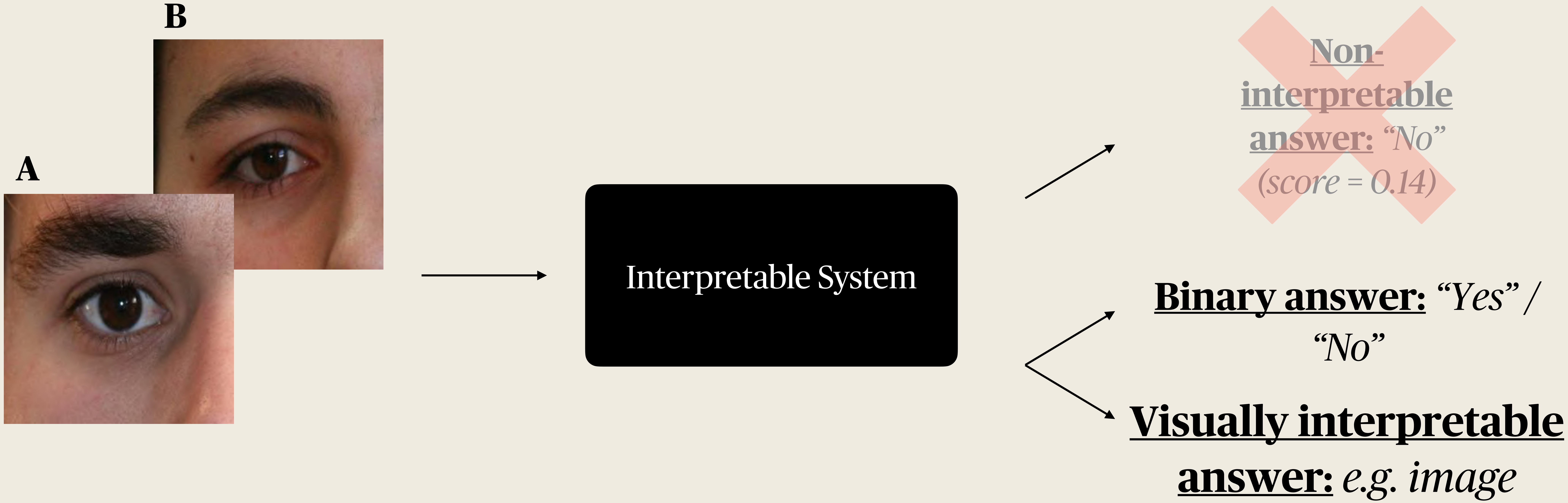

Figure 1: Visualisation of the underlying problem.

Related Work

Related Work

Deep Learning - DenseNet

- **Densely connected** blocks (i.e. within each block, each node receives all the feature maps from the previous nodes)
- **Composition of operations** (e.g. BN, convolutions or pooling)
- Multiple **information pathways**
- Addition of "**transition layers**" in between dense blocks, to change the feature maps' sizes

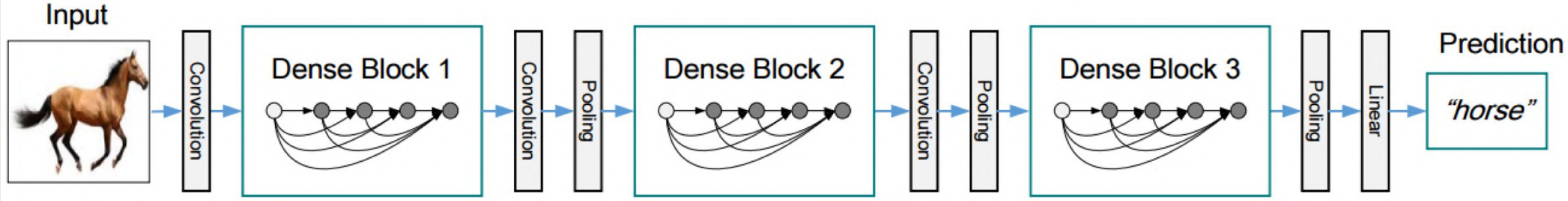

Figure 2: DenseNet architecture with three dense blocks [2].

Related Work

Deep Learning - Mask R-CNN

- Based on the **Faster R-CNN** architecture
- Use of a **RPN** to **propose object regions**
- **Three branches** (classification, regression and segmentation)
- Introduction of **RoIAlign** to **extract the region proposal's feature maps** from the common feature map
- Useful for **instance segmentation** and even **pose estimation**

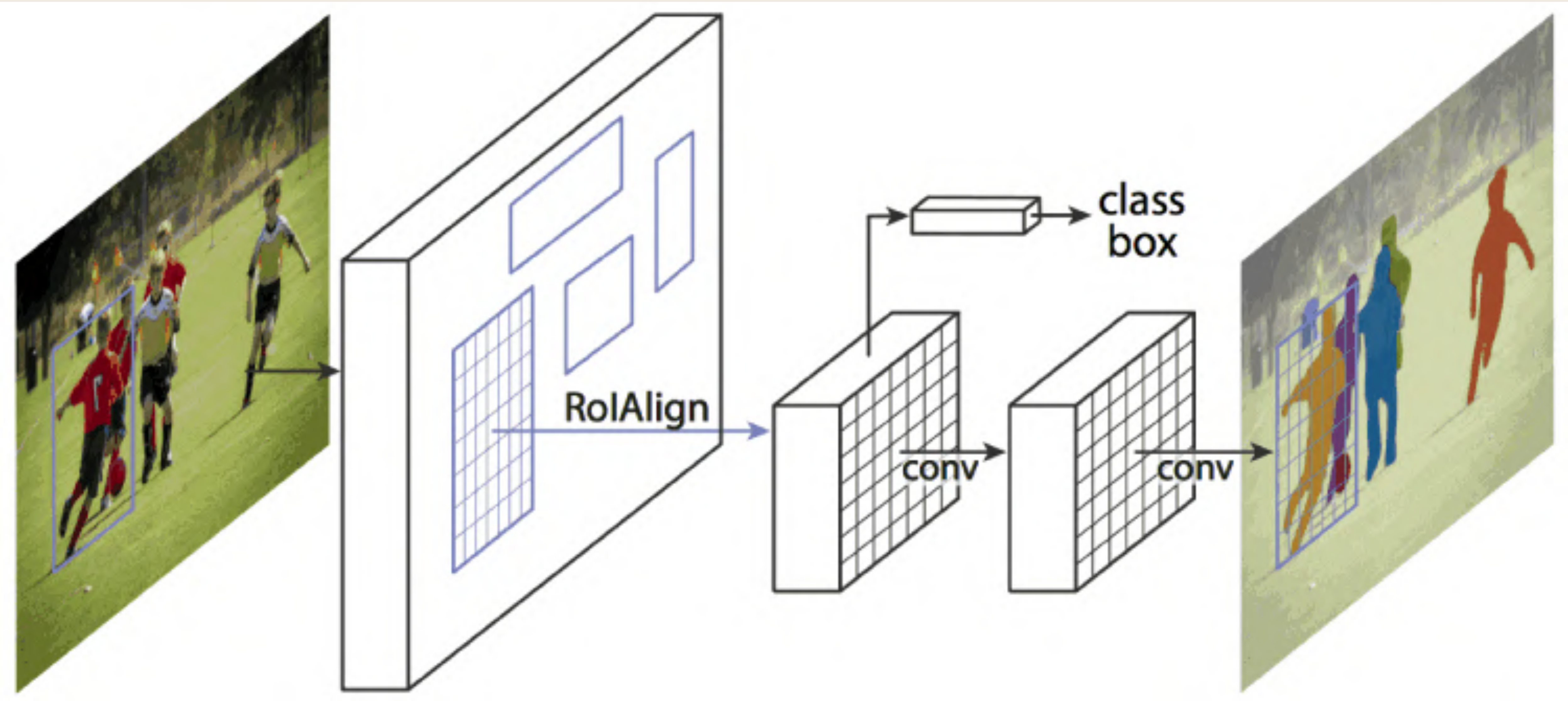

Figure 3: Mask R-CNN architecture, with the small FCN and RoIAlign highlighted [3].

Related Work

Deep Learning - StyleGAN2

- Use of a **mapping network** to map the original latent space (*Z*) to an intermediate, more **disentangled** one (*W*)
- Notion of "**style**", to condition the generation process
- **Incorporation of noise** to add further detail
- **Specifically on StyleGAN2, replacement of progressive growing with input/output skips** to enable the use of multiple resolutions (i.e. keep the advantages of PG) but only if it becomes useful (i.e. thus freeing the networks to use the resolutions as required)

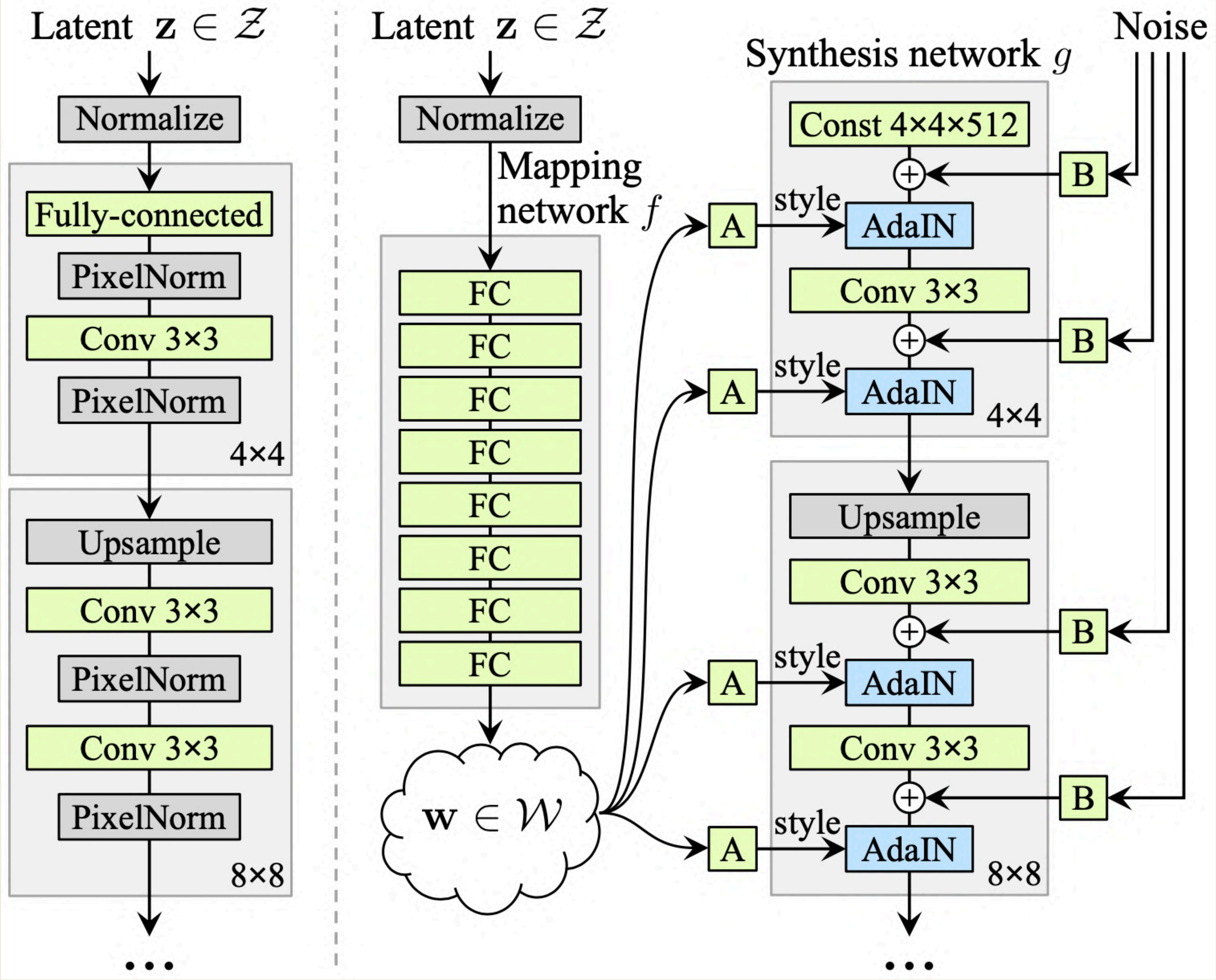

Figure 4: ProgGAN and StyleGAN architectures [4].

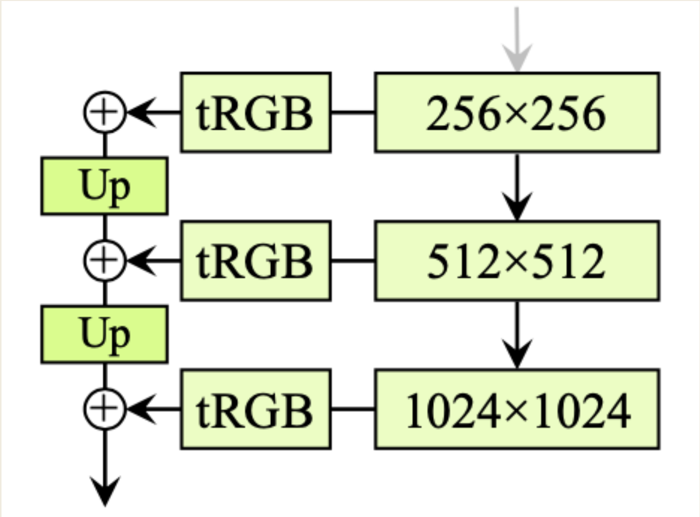

Figure 5: Revised generator architecture for StyleGAN2 [5].

Related Work

ML Interpretability - **L**ocal **I**nterpretable **M**odel agnostic **E**xplanations

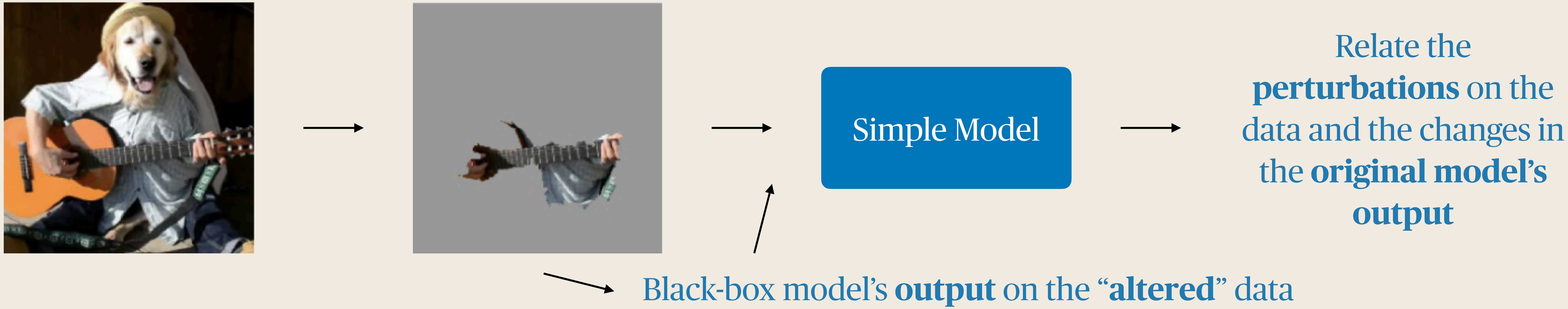

Figure 6: Overview of LIME's explanation process.

$$explanation(x) = \arg\min_{g \in G} \underbrace{L(f, g, \pi_x)}_{\text{Loss}} + \underbrace{\Omega(g)}_{\text{Complexity}}$$

Figure 7: Equation that formally represents an explanation [6].

Related Work

ML Interpretability - Kernel **SH**apley **A**dditive ex**P**lanations

1. Sample ***K*** coalitions: $z'_k \in \{0,1\}^M$
2. Obtain **predictions** for each z'_k by using $f(h_x(z'_k))$
3. Compute the **weight** for each z'_k with equation 2.20
4. Fit the **weighted linear model** using equation 2.18
5. Return the **coefficients** from the linear model, namely, the **Shapley values** ϕ_i

$$\pi_x(z') = \frac{(M-1)}{\binom{M}{|z'|}|z'|(M-|z'|)} \tag{2.20}$$

$$L(f,g,\pi_x) = \sum_{z' \in Z} [f(h_x(z')) - g(z')]^2 \pi_x(z') \tag{2.18}$$

Figure 8: The top equation defines the SHAP Kernel, which gives more or less weight to small / large coalitions. The bottom equation defines the loss function when using KernelSHAP [7].

Approach with LIME/SHAP

Approach with LIME/SHAP

1. Traditional **CNN-based classification** of the test pair **(G**enuine or **I**mpostor)
2. **Prediction interpretation** using interpretability techniques (e.g. **LIME**, **KernelSHAP**, etc...)

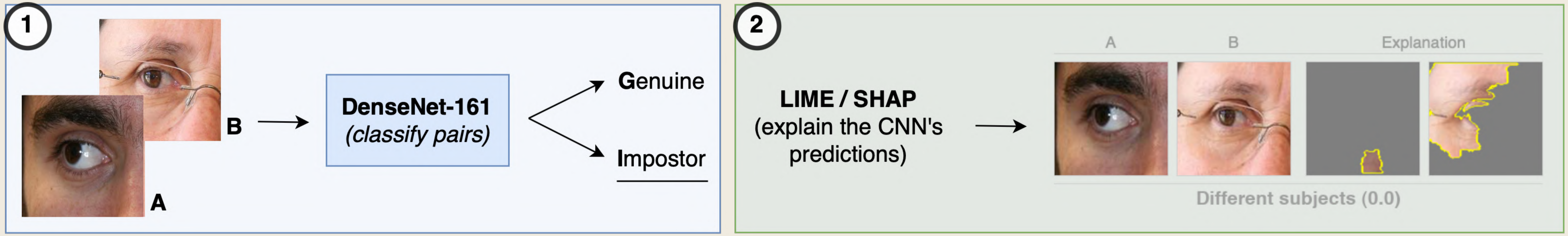

Figure 9: Results obtained with LIME / SHAP on top of a traditional CNN.

Approach with LIME/SHAP

Figure 10: Genuine pairs correctly classified by the CNN.

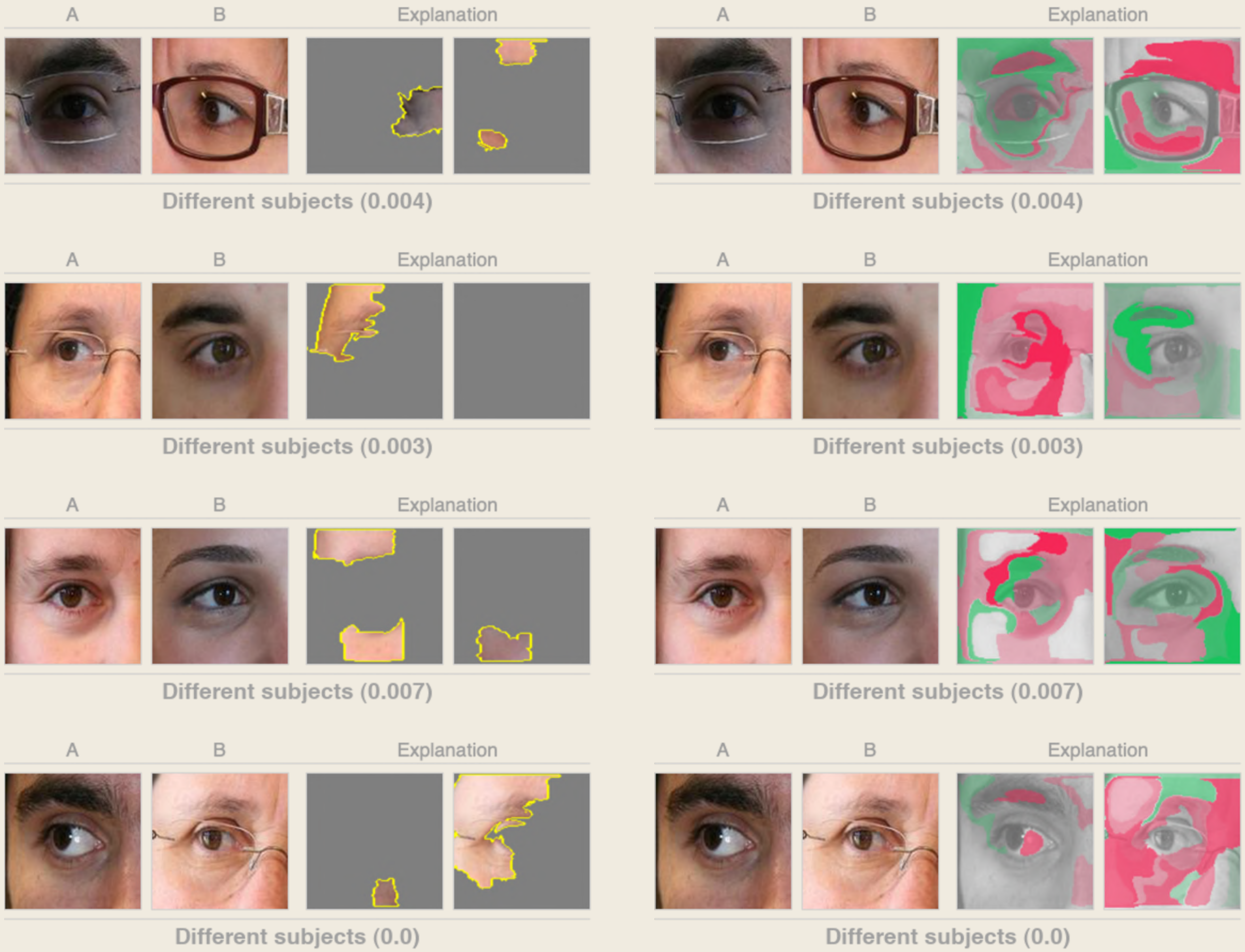

Figure 11: Impostor pairs explained with LIME (on the left) and KernelSHAP (on the right).

Proposed Method

Proposed Method

1. Traditional **CNN-based classification** of the test pair (**G**enuine or **I**mpostor)
2. **Segmentation** of iris, sclera and eyebrow
3. **Synthetic pair** generation and **segmentation**
4. **Comparison and gathering** of the ***K*** closest synthetic pairs (i.e. neighbours)
5. **Pixel difference** between the test image ***B*** and the neighbours' images ***B***

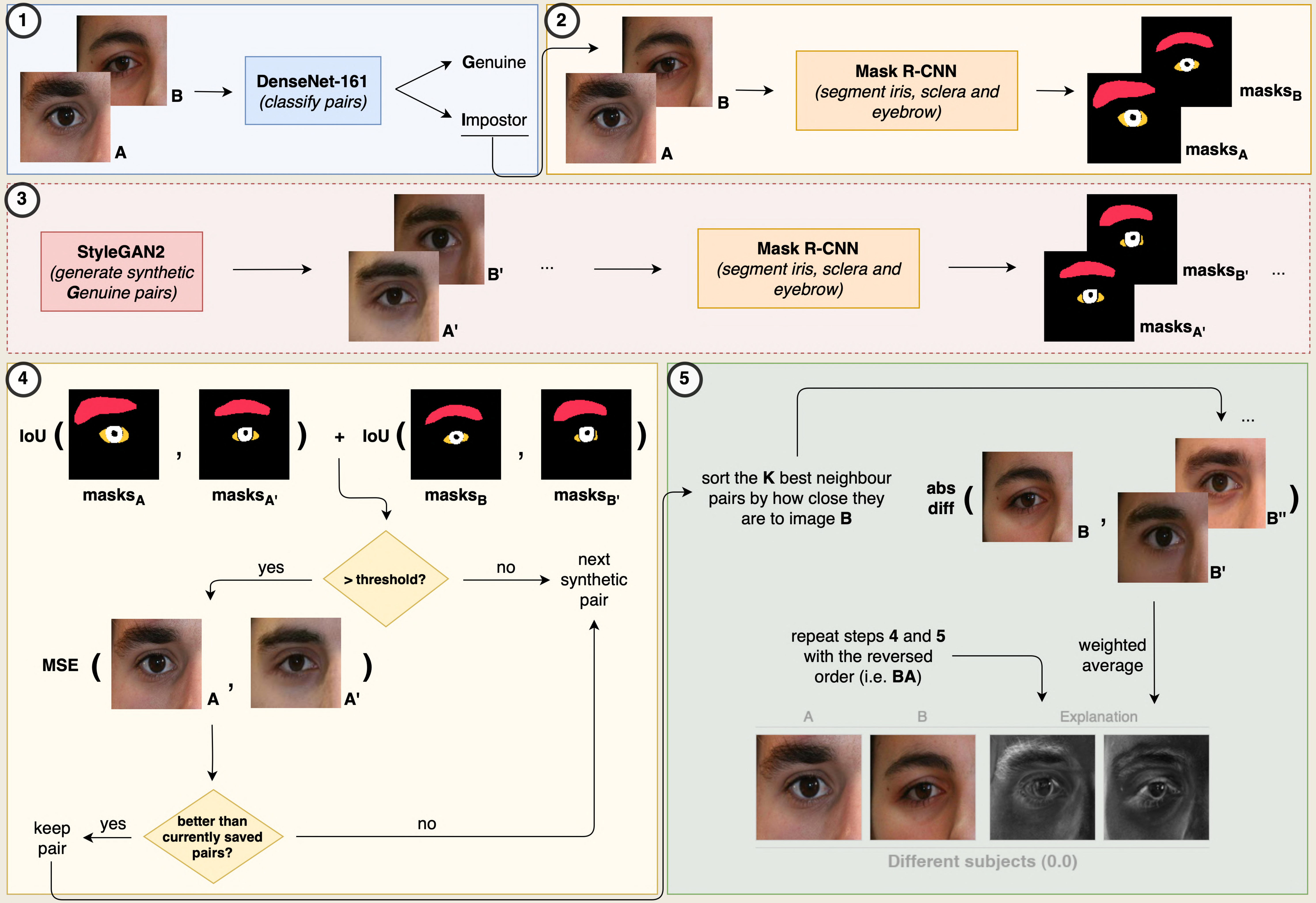

Figure 12: Diagram of the main pipeline.

Proposed Method

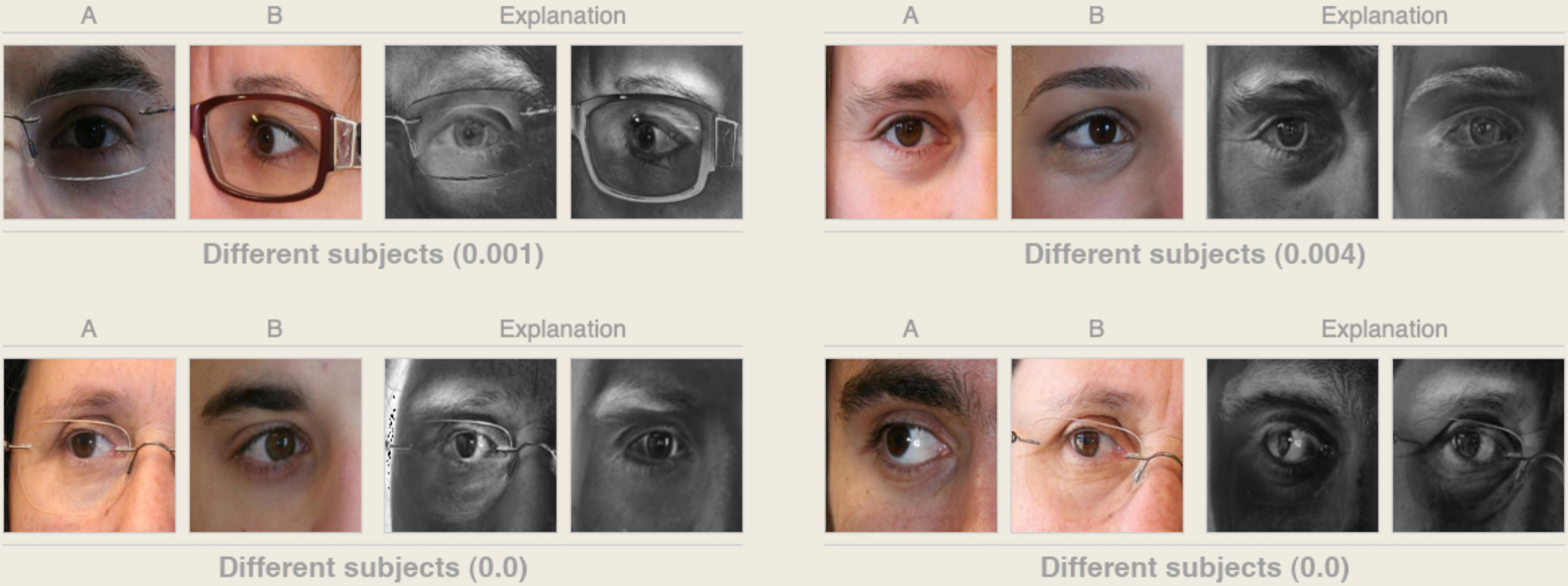

Figure 13: Results obtained with the first method (directly comparable to LIME/SHAP).

Proposed Method

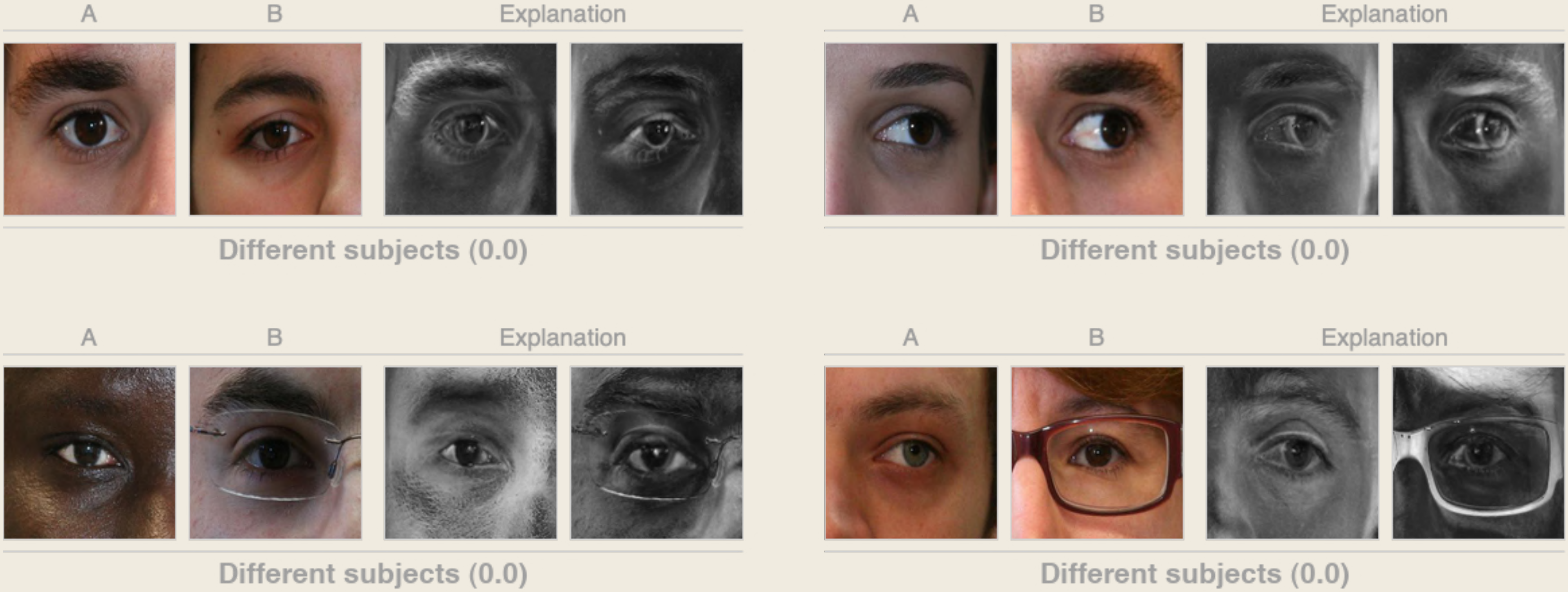

Figure 14: Results obtained with the first method.

Ongoing and Future Tasks

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- Use **other techniques** besides IoU
- Add **captions** to the visual explanations (i.e. a text representation)
- Make **speed** improvements
- Consider **other approaches** (possibly based on **latent space directions**)

Conclusion

Any questions?

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