

BIOMETRICS UNDER ATTACKS

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23rd International Conference on Security and Cryptography



GREYC

Electronics and Computer Science Laboratory



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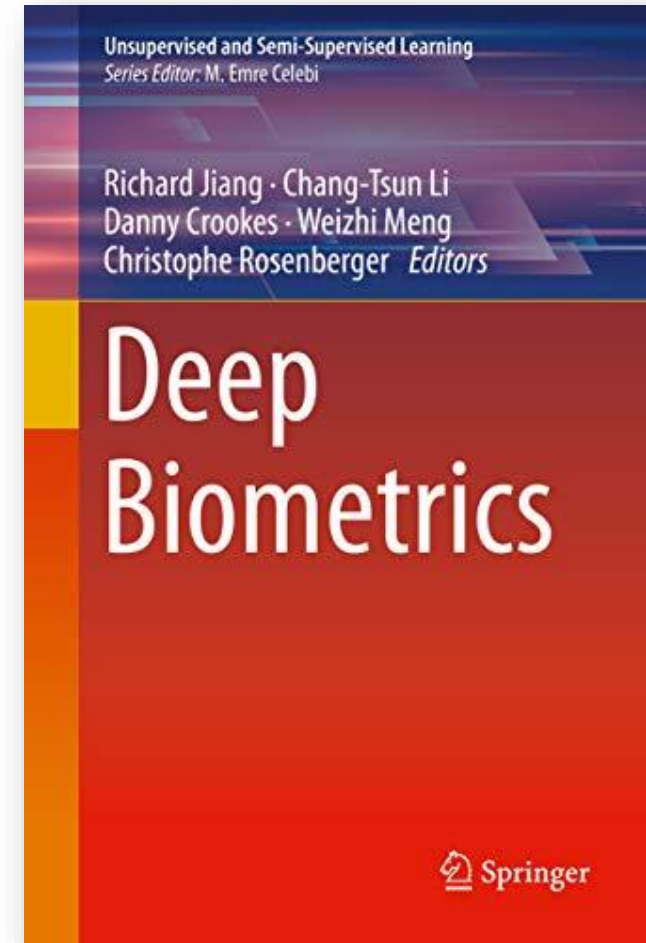
WHO AM I?

Christophe ROSENBERGER

- ❑ Full professor in Computer Science at ENSICAEN - FRANCE
- ❑ Cybersecurity researcher in the GREYC research lab
 - ✓ Biometrics (since 2005)
 - ✓ Digital forensics (since 2021)
- ❑ Reviewer in charge of the evaluation/monitoring of the SERICS foundation (2022-2026)



SERICS
SECURITY AND RIGHTS IN THE CYBERSPACE



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PLAN

- ❑ Motivations
- ❑ Presentation & injection attack (active)
- ❑ Template attack (passive)
- ❑ Backdoor & adversarial attack (active)
- ❑ Conclusion





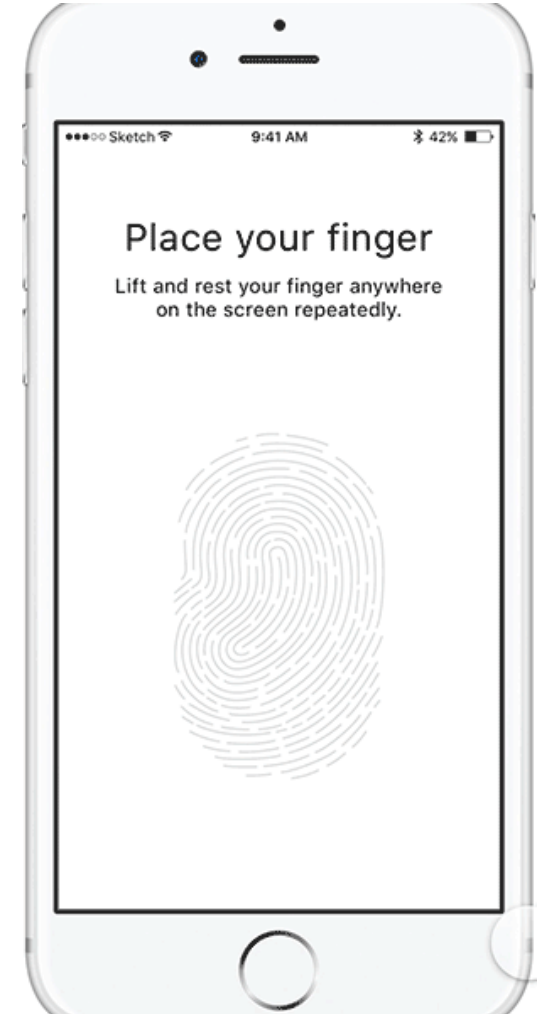
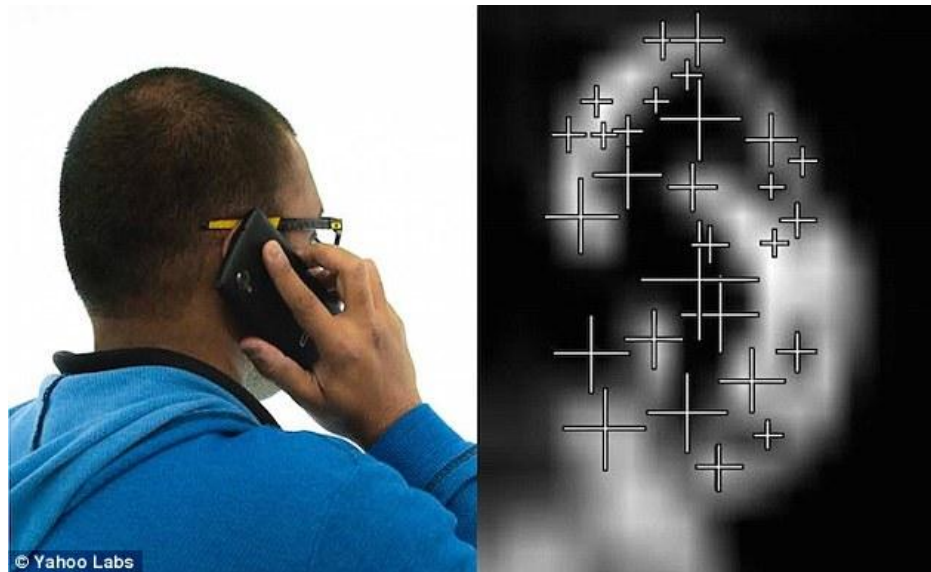
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BIOMETRICS

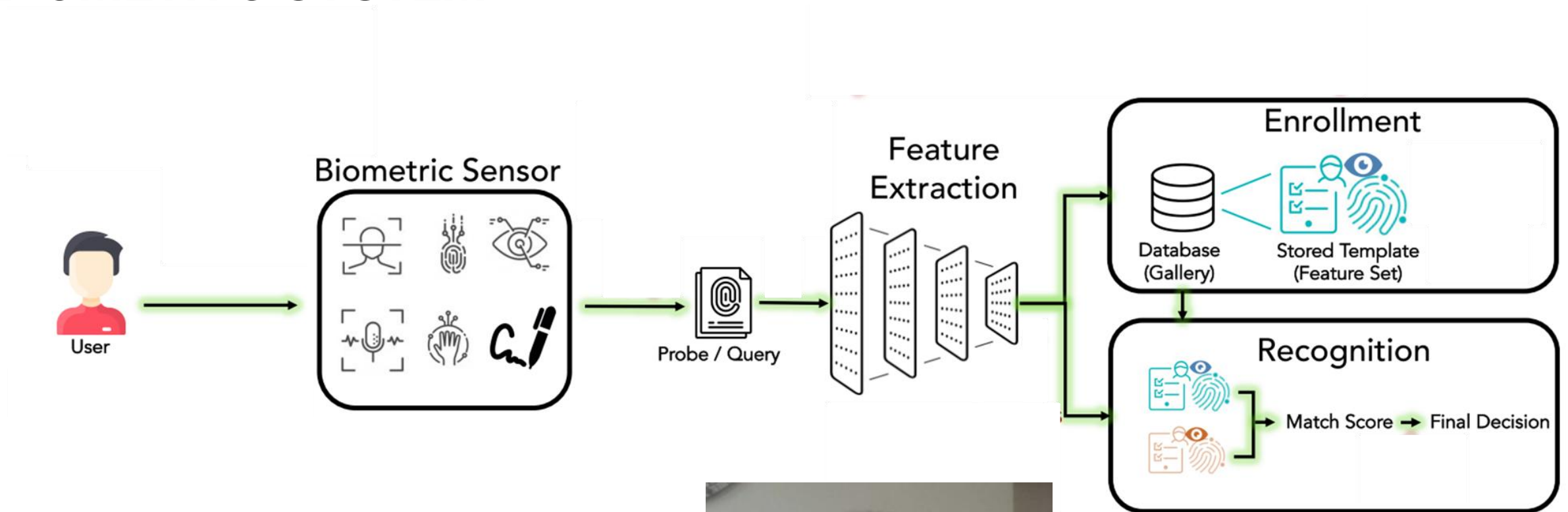
Automatic identification of an individual or verification of its identity by using morphological or behavioral characteristics



APPLICATIONS



BIOMETRIC SYSTEM



Artificial Intelligence, a key component:

- ❑ Preprocessing (e.g. face detection)
- ❑ Efficient feature extraction
- ❑ Simple and fast comparison



CERTIFICATION

A product certification ensures that the system can be trusted to work accurately, even under challenging circumstances.



Biometric security



Biometric component



ISO 19795-1
ISO 30107-3



Biometric system on card (BSOC)

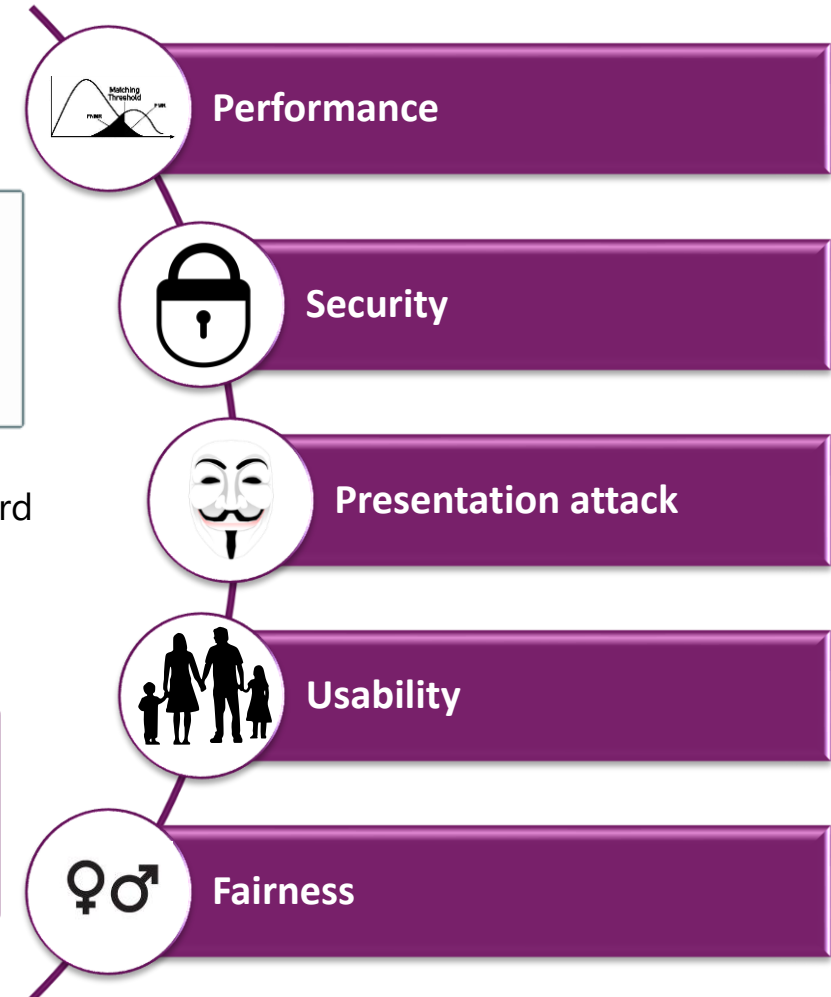


NIST/NVLAP

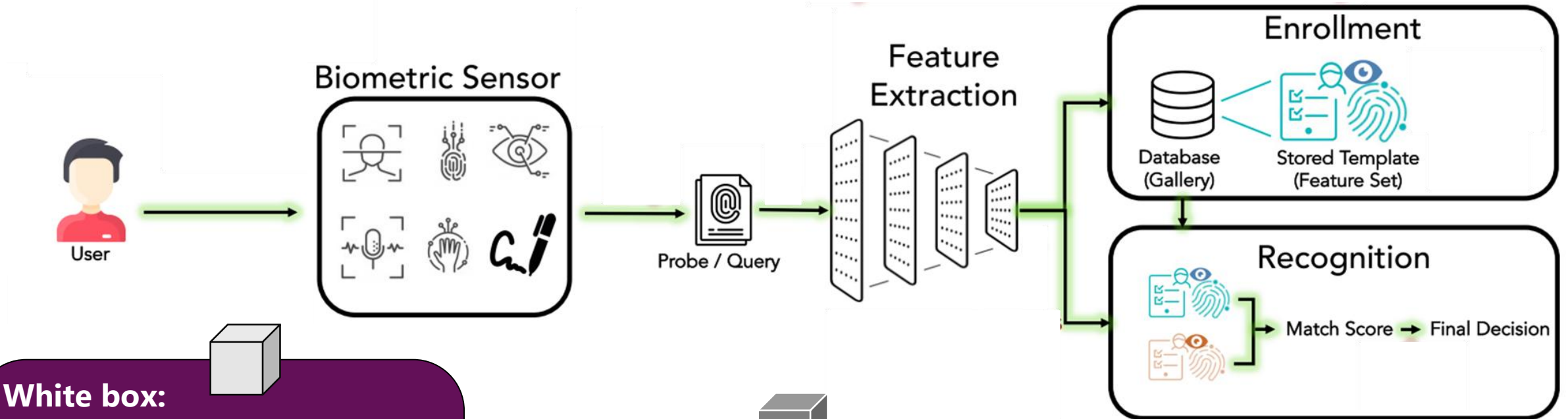


Biometric system on card (VBSS)

- ❑ Requirements defined by an international authority of stakeholders from industry, government, and subject matter experts ;
- ❑ Tests done by an independent accredited laboratory ;
- ❑ Attacks are useful for testing biometric systems.



THREAT MODEL



White box:

- ❑ **Access:** everything (code, coefficients, score...)
- ❑ **Realism:** no (except If a BSP uses available deep models on Internet)
- ❑ **Difficulty:** easy

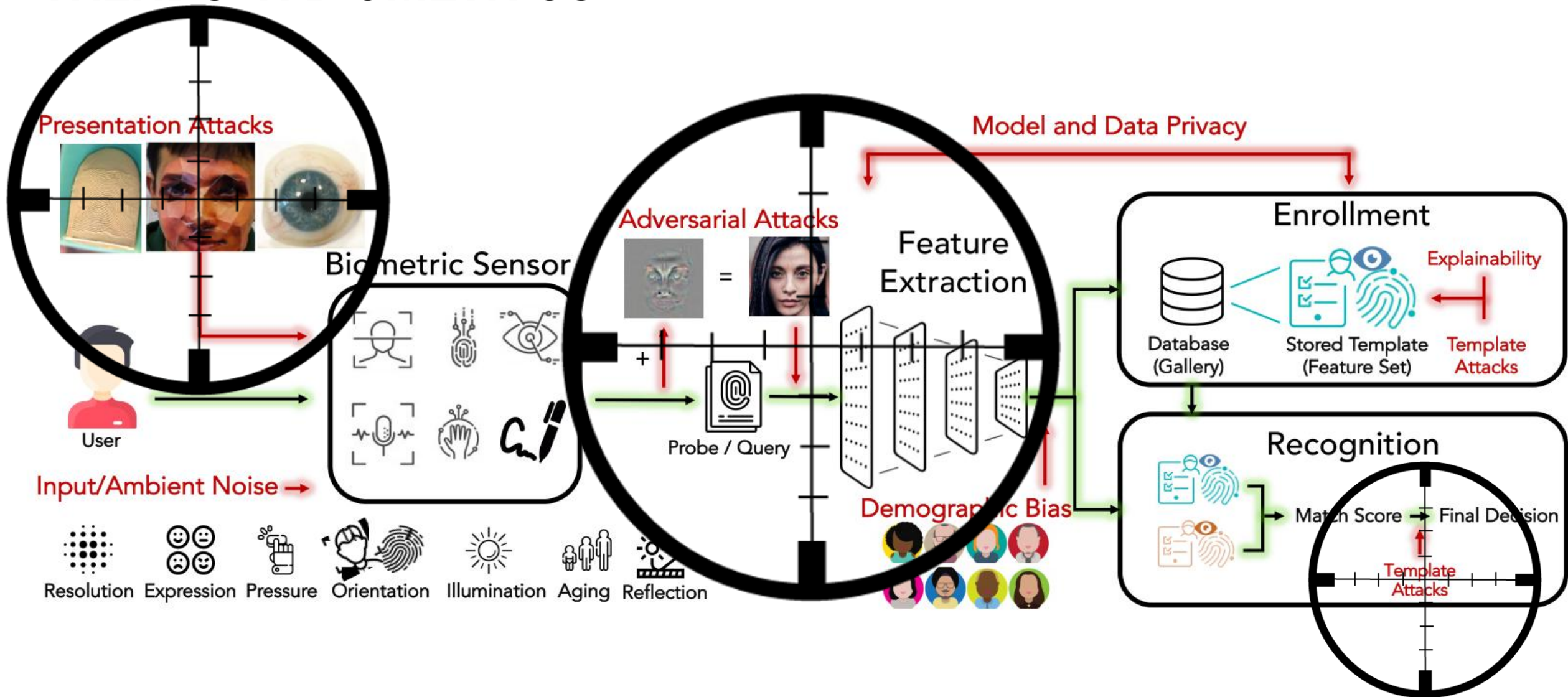
Gray box:

- ❑ **Access:** few information (score, decision)
- ❑ **Realism:** yes (certification)
- ❑ **Difficulty:** average

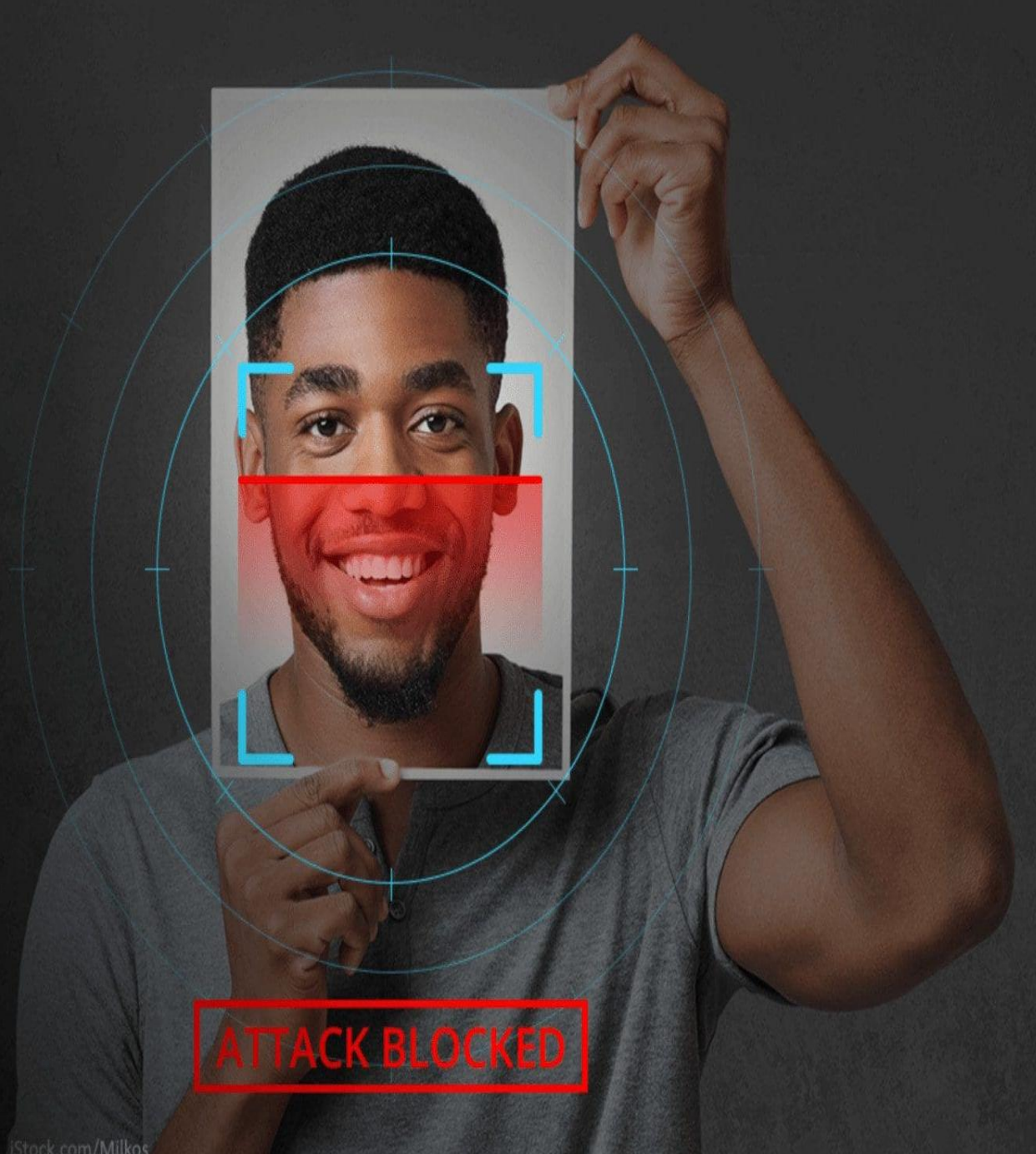
Black box:

- ❑ **Access:** only decision
- ❑ **Realism:** yes (daily life)
- ❑ **Difficulty:** high

TRENDS IN BIOMETRICS



Jain, A. K., Deb, D., & Engelsma, J. J. (2021). Biometrics: Trust but verify. *IEEE Transactions on Biometrics, Behavior, and Identity Science*, 4(3), 303-323.



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PRESENTATION & INJECTION ATTACKS

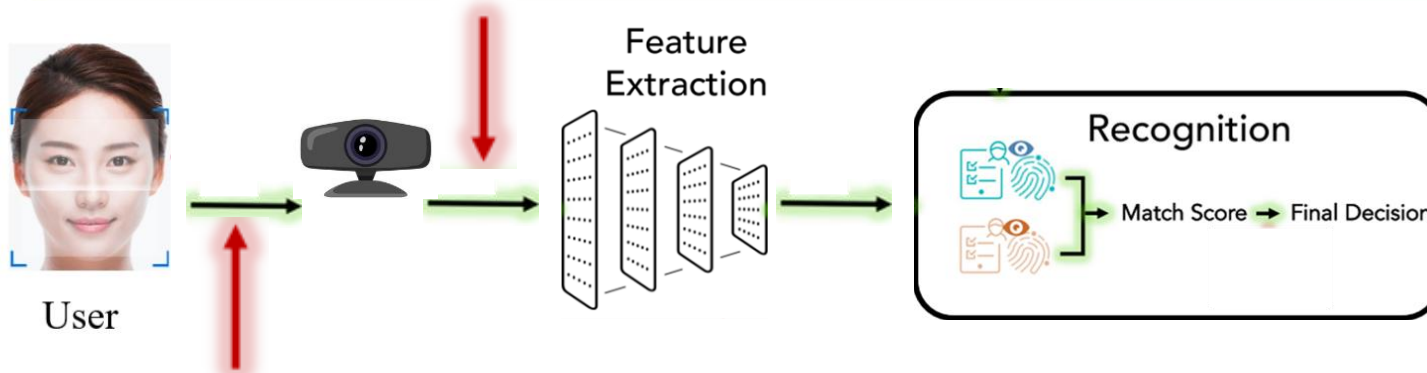
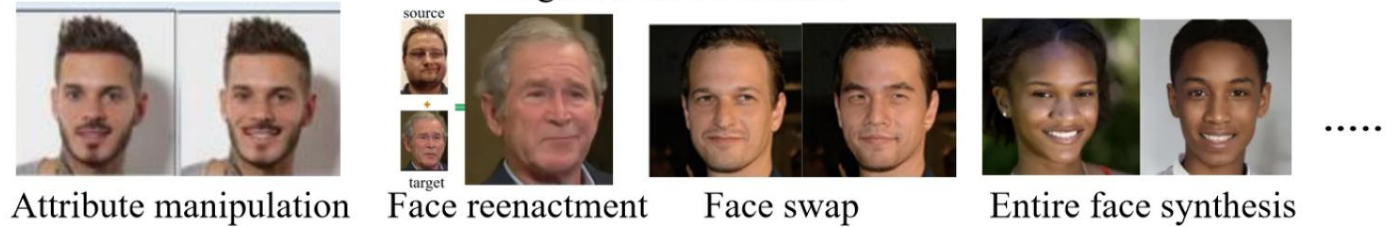


*Avoiding the good functioning
of a biometric system through
the capture*



PRESENTATION/INJECTION ATTACKS

Digital Domain Attack



Physical Domain Attacks



Two categories:

❑ Physical attack

Present to the sensor an altered content to the sensor.

❑ Digital attack

Altering the multimedia content with AI injected to the device or through a link.

Günay Yılmaz, A., Turhal, U., & Nabyev, V. (2023). Face presentation attack detection performances of facial regions with multi-block LBP features. *Multimedia Tools and Applications*, 82(26), 40039-40063.

PRESENTATION ATTACKS

Definitions:

☐ **Presentation attack**

Presentation to the biometric capture subsystem with the goal of interfering with the operation of the biometric system

☐ **Presentation Attack Instrument (PAI)**

Biometric characteristic or object used in a presentation attack



James Bond movie
Diamonds are forever (1971)

007™



Objectives:

☐ **Identity concealer**

Subversive biometric capture subject who attempts to avoid being matched to their own biometric reference

☐ **Identity impersonation**

Attempt to be matched as another individual

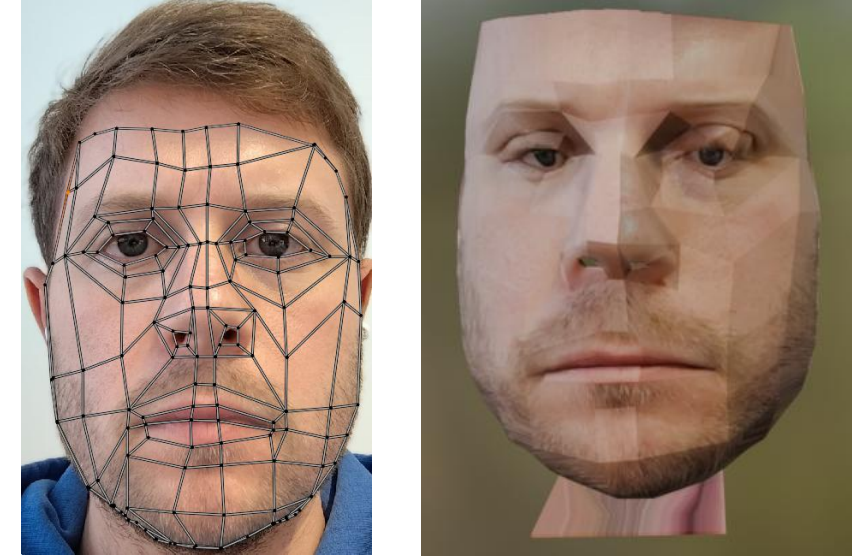
FACE PRESENTATION ATTACKS (1/3)



Simple PAI



Makeup (@Paolo Ballesteros)



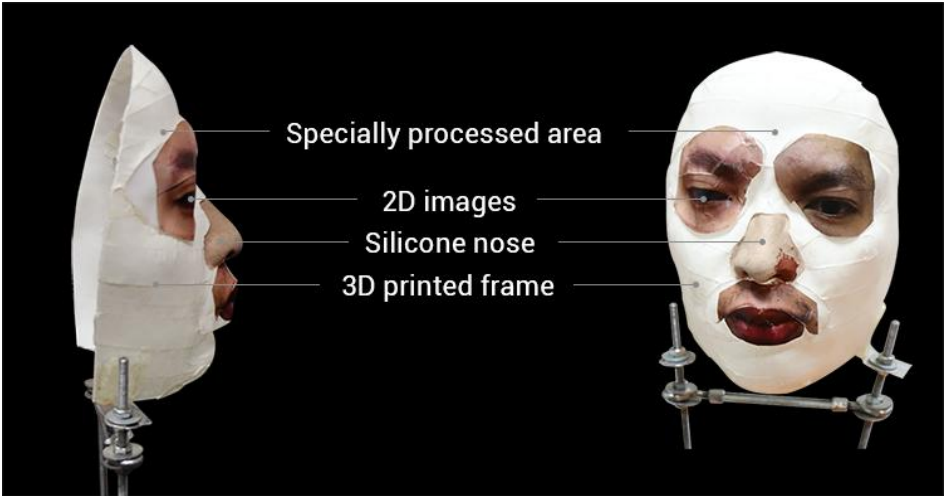
Papercut mask

[DEMO 1](#)

[DEMO 2](#)

Günay Yılmaz, A., Turhal, U., & Nabiye, V. (2023). Face presentation attack detection performances of facial regions with multi-block LBP features. *Multimedia Tools and Applications*, 82(26), 40039-40063.

FACE PRESENTATION ATTACKS (2/3)



3D spoof (Faceld attack)



3D scan



papercut



PVC (artist)



High quality mask

FACE PRESENTATION ATTACKS (3/3)

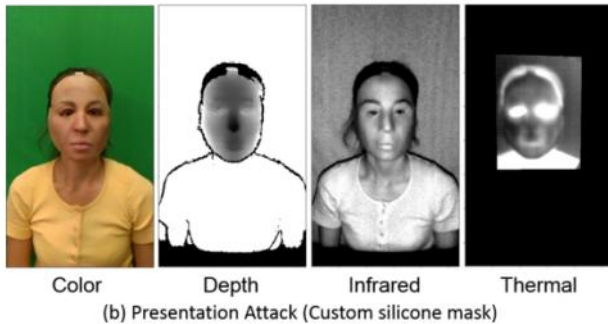
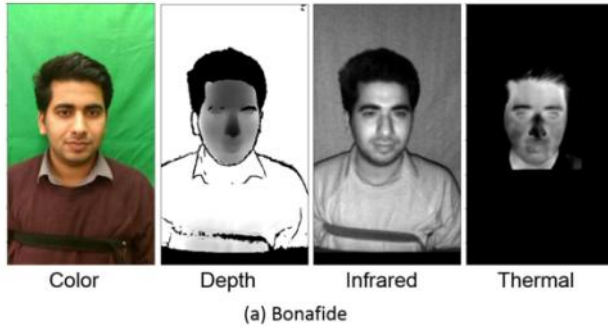


Deceased person



FACEPAD 3D

COUNTERMEASURE - PAD

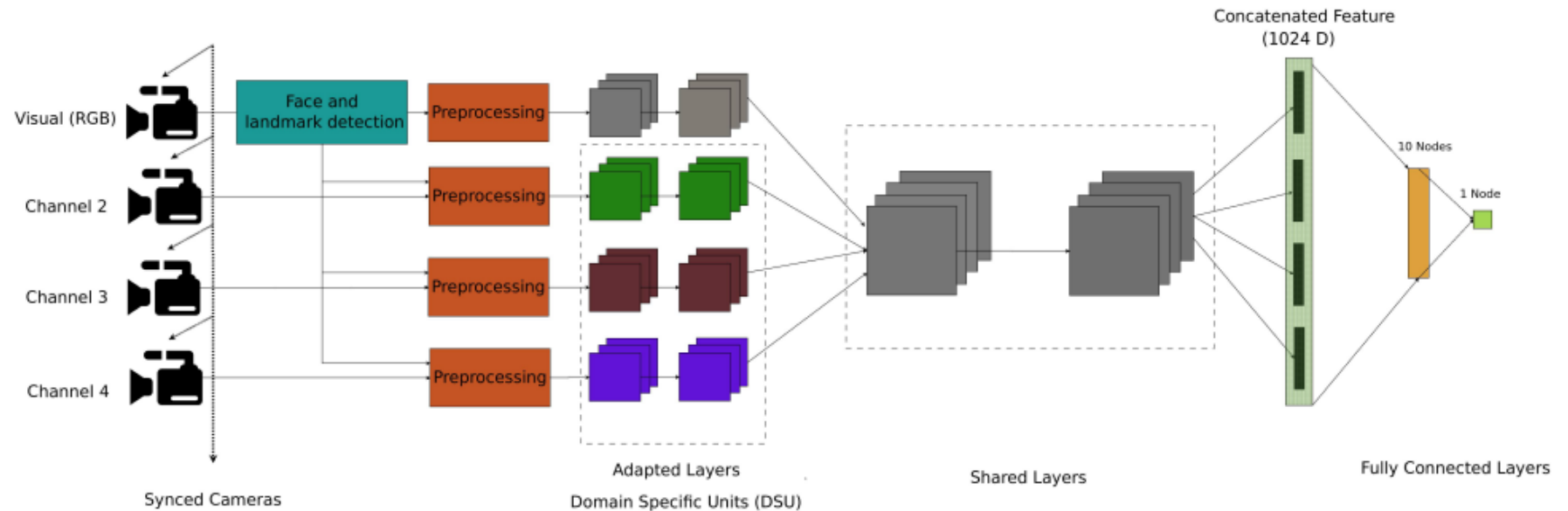


Presentation Attack Detection (PAD)

Automated determination of a presentation attack

Two main components

- ❑ **Sensor:** RGB, 3D information, infrared, thermal...
- ❑ **AI:** deep models allowing to distinguish bona fide samples from an attack



George, A., Mostaani, Z., Geissenbuhler, D., Nikisins, O., Anjos, A., & Marcel, S. (2019). Biometric face presentation attack detection with multi-channel convolutional neural network. *IEEE transactions on information forensics and security*, 15, 42-55.



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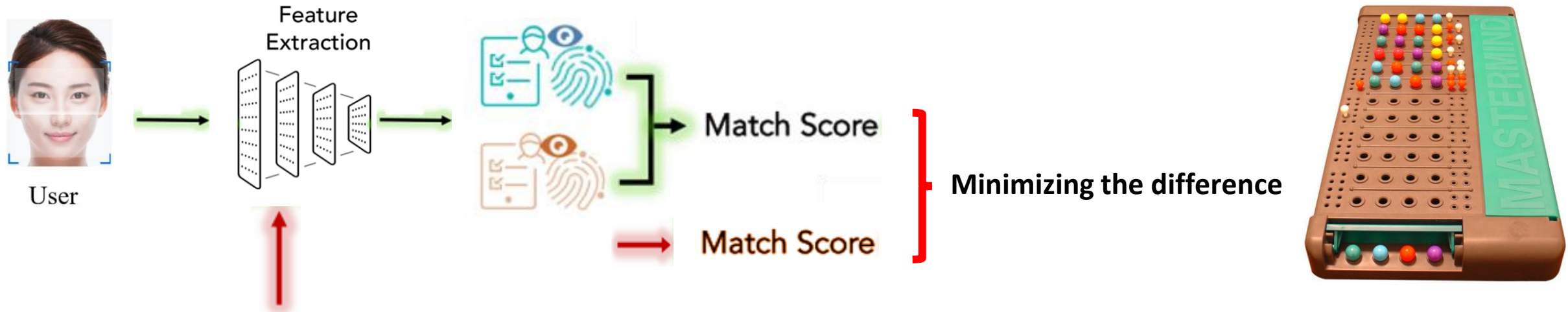
TEMPLATE ATTACKS



*Security and privacy breaches
from biometric templates*



SIDE CHANNEL ATTACKS (SECURITY)



Observing the biometric system:

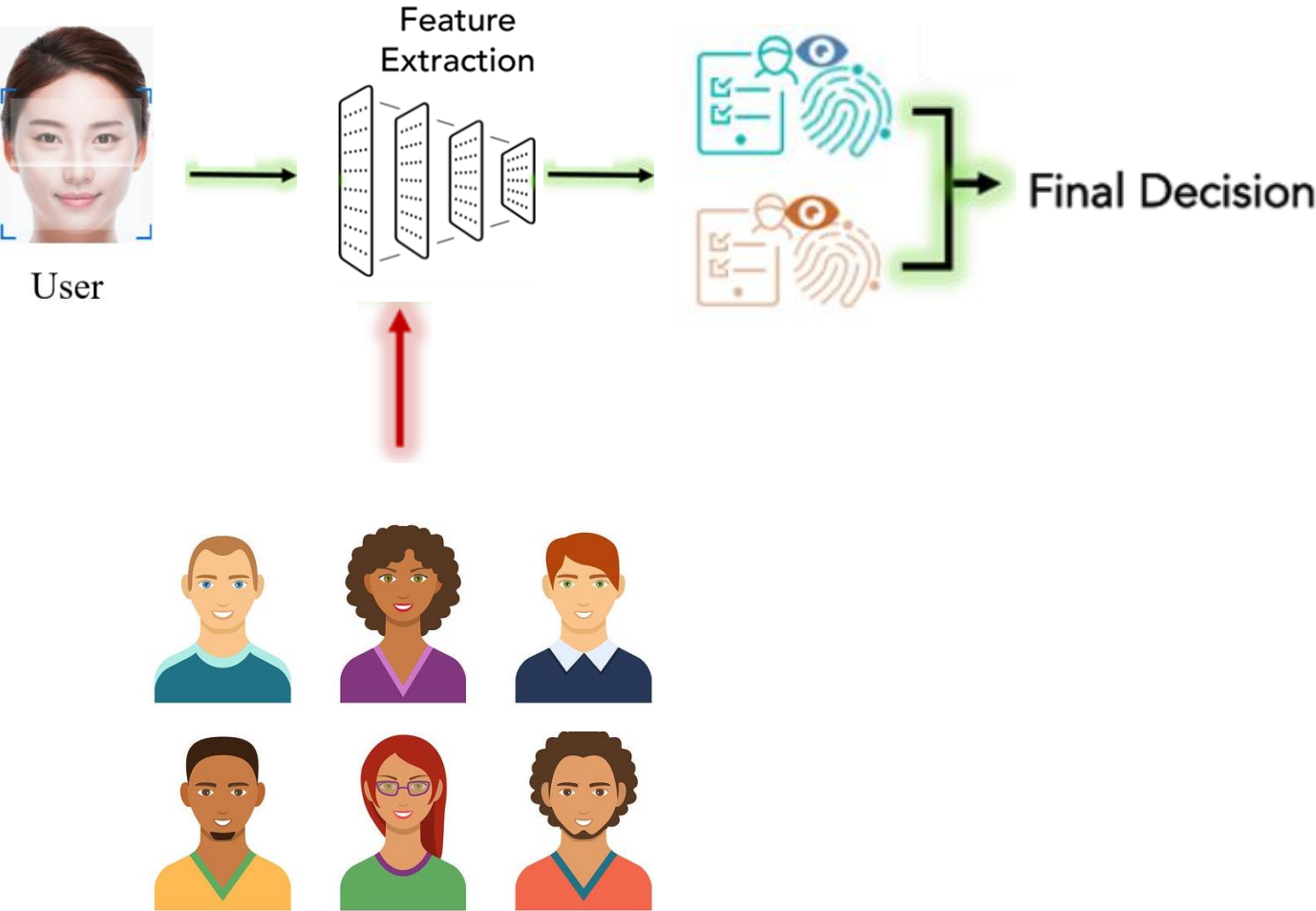
- ❑ White box: templates value

Possible inversion of the deep model to recover the reference template

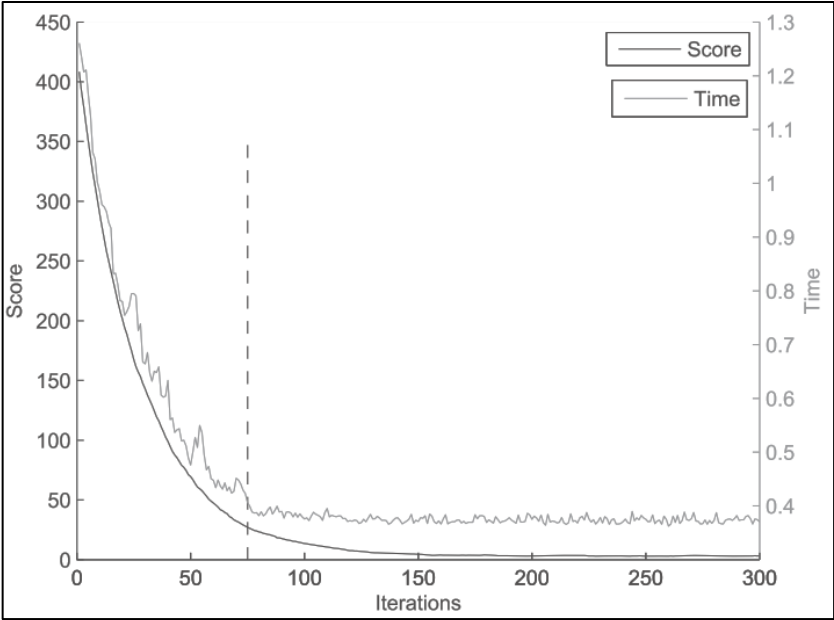
- ❑ Gray box: match score

In industrial biometric systems (such as smartphones), the match score is never displayed (only the decision) for security reasons

SIDE CHANNEL ATTACKS (SECURITY)

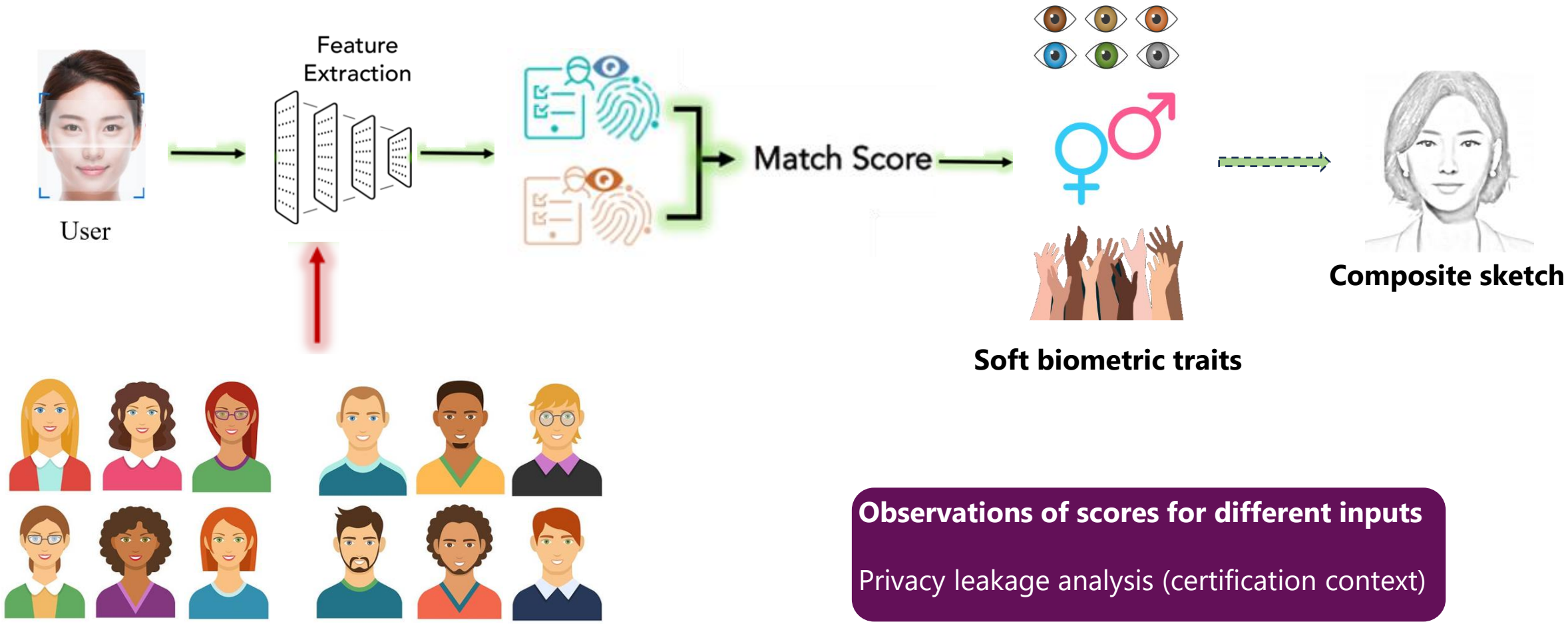


Black box systems: comparison time
Less relevant nowadays with AI



Galbally, Javier. "A new Foe in biometrics: A narrative review of side-channel attacks." Computers & Security 96 (2020).

DIFFERENTIAL PRIVACY

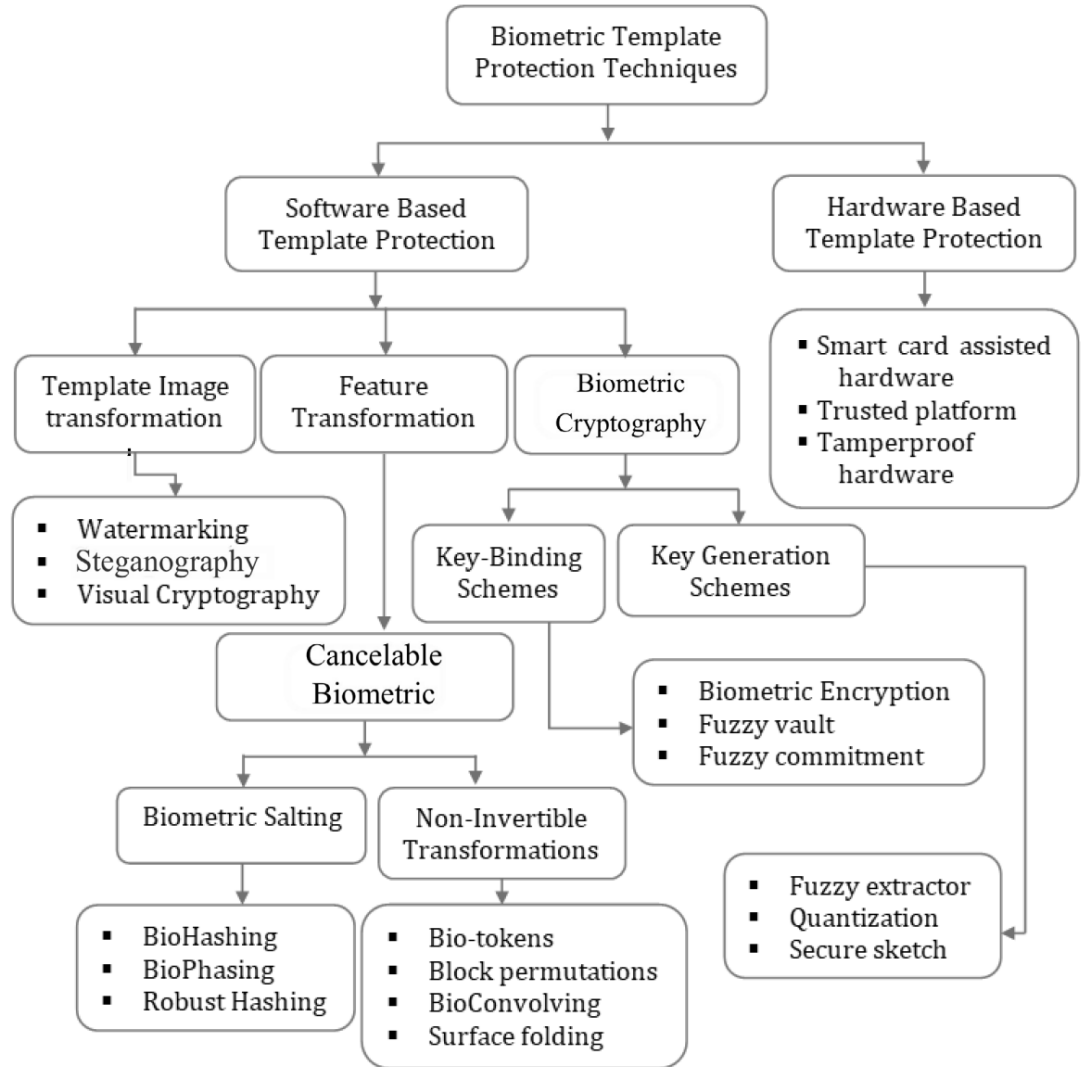


COUNTERMEASURE - BTP

Biometric Template Protection (BTP): Privacy Enhancing Technology (PET)

Taxonomy of existing approaches:

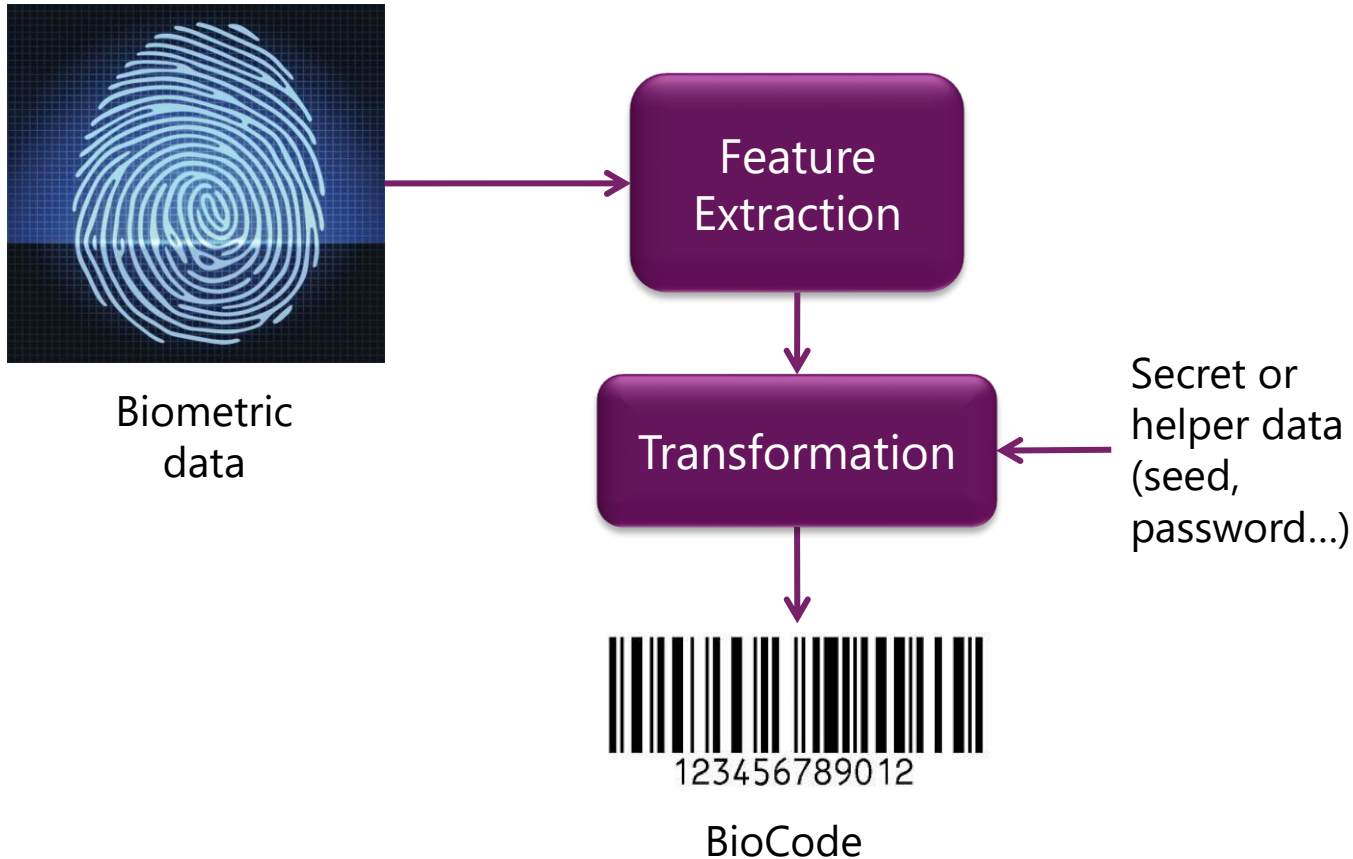
- ❑ Hardware solutions
- ❑ Software template protection



Sardar, A., Umer, S., Pero, C., & Nappi, M. (2020). A novel cancelable facehashing technique based on non-invertible transformation with encryption and decryption template. *IEEE Access*, 8, 105263-105277.

COUNTERMEASURE - BTP

Cancelable biometrics:



Expected properties:

- ❑ **Verifiability:** it is possible to authenticate a user given a BioCode
- ❑ **Revocability:** it is possible to renew the BioCode in case of attack
- ❑ **Non invertibility or irreversability:** impossible to recover the raw biometric data given the BioCode and the Secret
- ❑ **Undistinguishability:** impossible to distinguish impostor BioCodes from legitimate ones with different Secrets
- ❑ **Unlikability:** no information leakage from different legitimate Biocodes

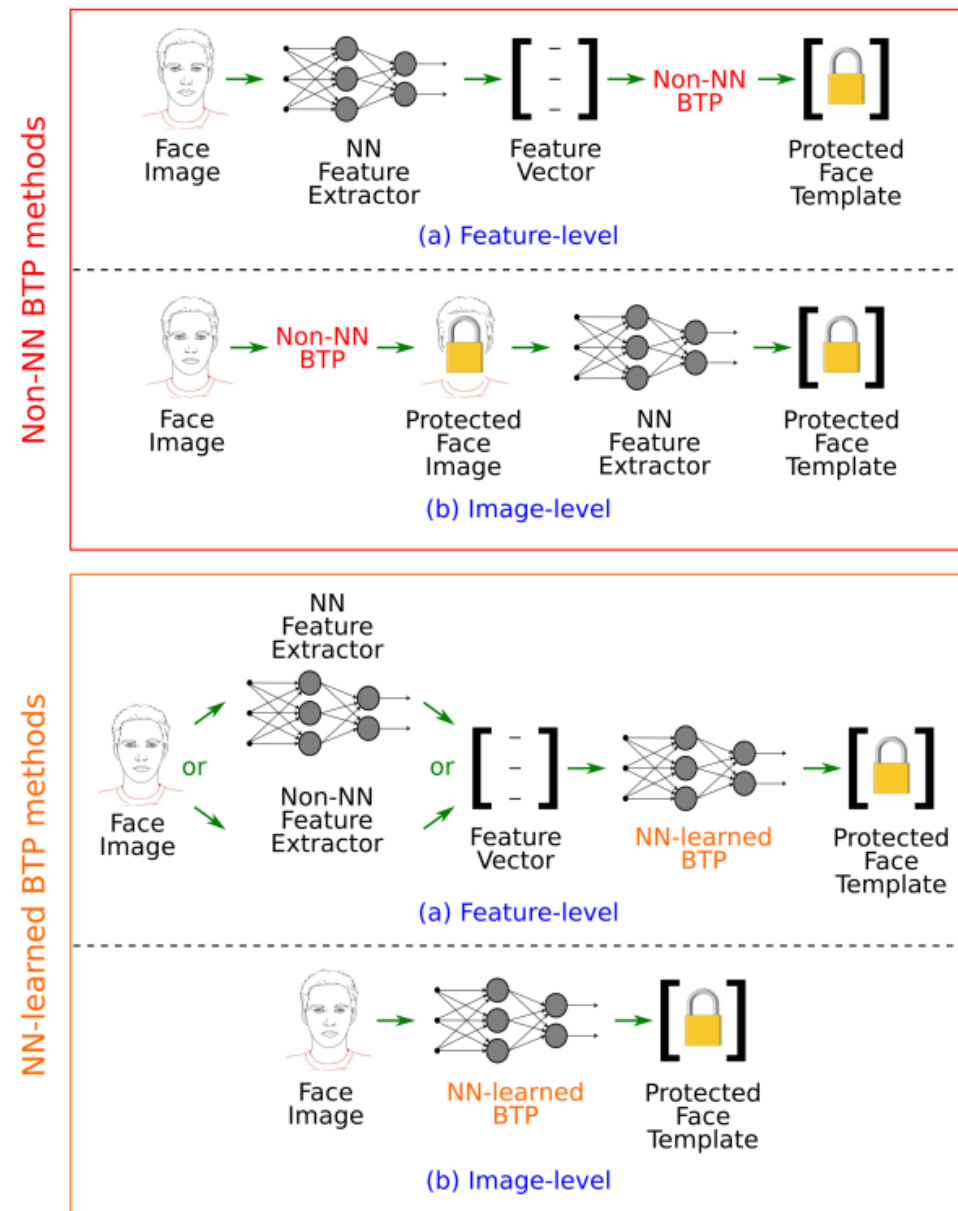
Lacharme Patrick, Cherrier Estelle and Rosenberger Christophe. Preimage attack on biohashing. In : *2013 International Conference on Security and Cryptography (SECRYPT)*. IEEE, 2013. p. 1-8.

COUNTERMEASURE - BTP

AI based BTP:

- ❑ Feature generation more efficient with AI
- ❑ Deep networks can learn encrypted data (homomorphic)
- ❑ Generation of secure biometric signatures

V. Krivokuca Hahn and S. Marcel, “Biometric template protection for neural-network-based face recognition systems: A survey of methods and evaluation techniques,” IEEE Transactions Information Forensics Security, vol. 18, pp. 639–666, 2023



➤ Biometric Template Protection

Enrolled ✓

 ENROLL YOUR FACE CHOOSE A FACE TO ENROLL

Protection method

BioHashing – Case [1]*

Method properties

Probe key

Same Key

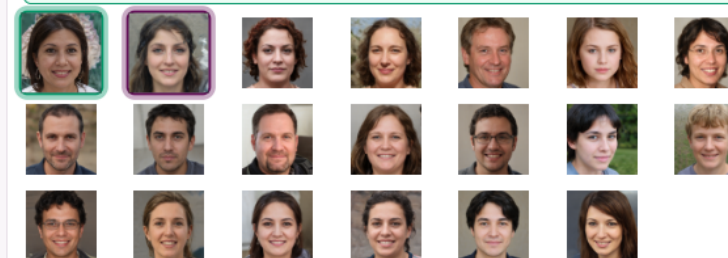
EER	AUC	THRESHOLD
-----	-----	-----------

3.76% 0.990 0.3951

Computed offline – VGGFace2 val · 60 identities × 10 images.

* Case labels refer to the Hahn & Marcel (2022) taxonomy

Switch face anytime – results update instantly



ENROLLMENT



PROBE



DIFF



✔ 300/512 bits match (58.6%) ✖ Hamming distance: 41.4%

DEMO

Score



Access Denied

0.4141 Hamming

Threshold: 0.3951

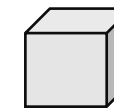
99 ms





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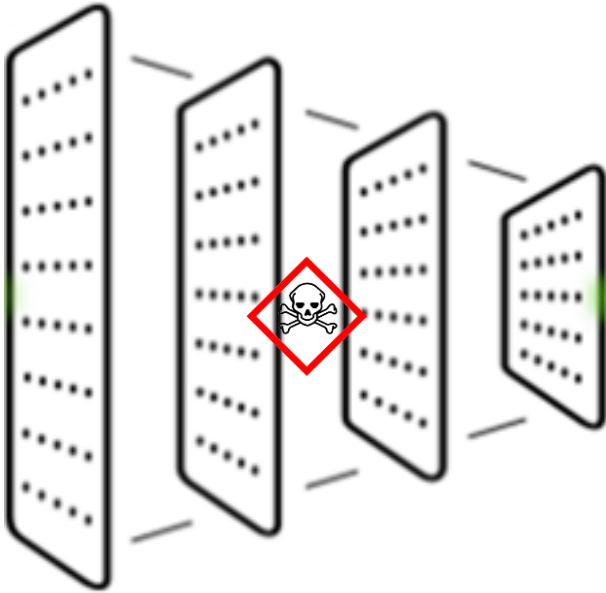
BACKDOOR & ADVERSARIAL ATTACKS



Manipulation of deep models by deliberately feeding them deceptive data to cause incorrect or unintended behavior



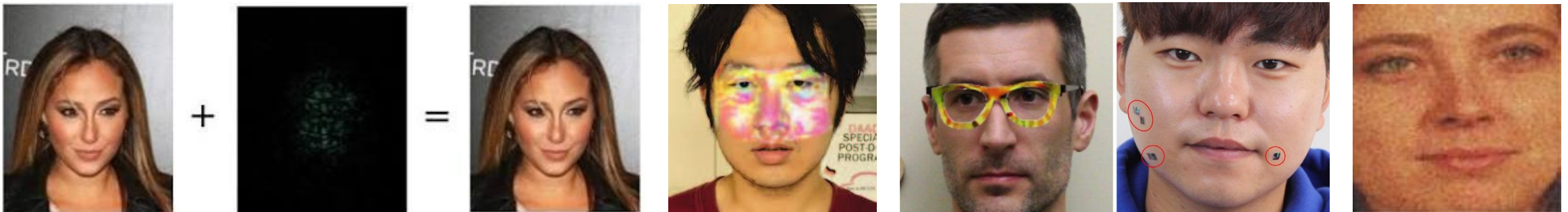
DATA POISONING



Deep models: Large use in biometrics for detection (i.e. face detection) and template extraction

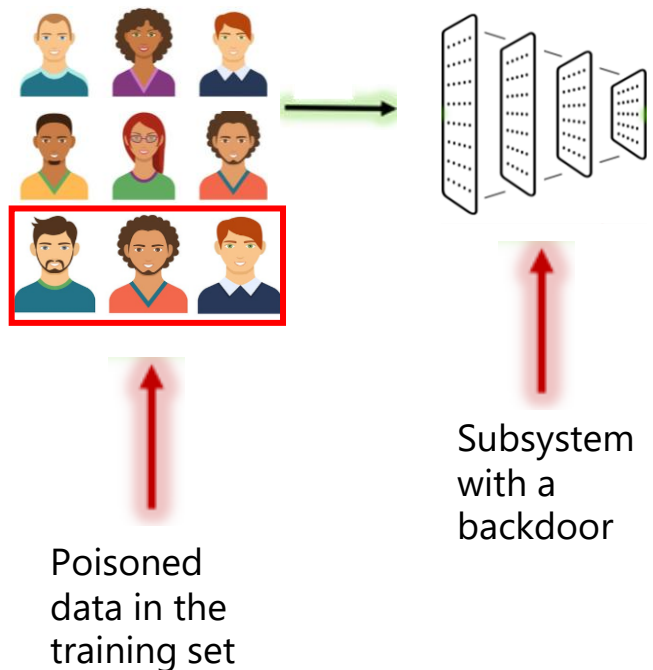
Principle:

- ❑ Alter an input image with a visible/invisible and physical/digital trigger
- ❑ During training (backdoor) or use (adversarial)
- ❑ Can be targeted to a specific user

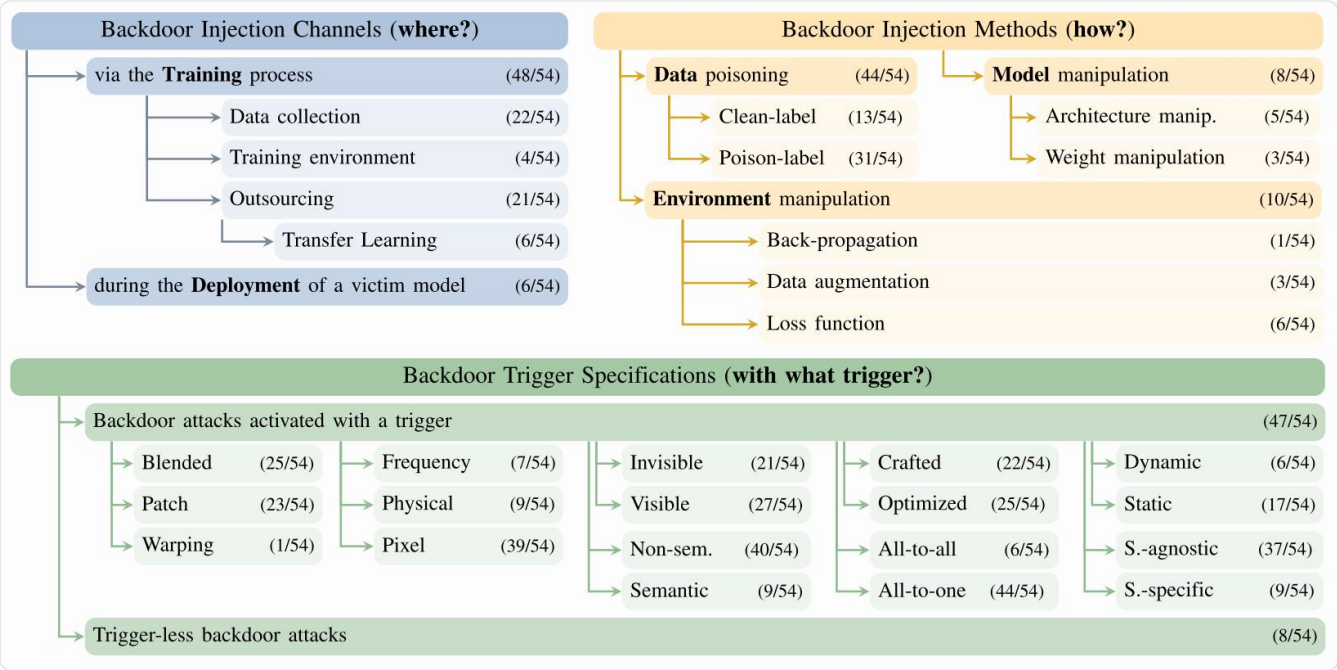


Xu, Y., Raja, K., Ramachandra, R., & Busch, C. (2022). Adversarial attacks on face recognition systems. In *Handbook of Digital Face Manipulation and Detection: From DeepFakes to Morphing Attacks* (pp. 139-161). Cham: Springer International Publishing.

BACKDOOR ATTACK

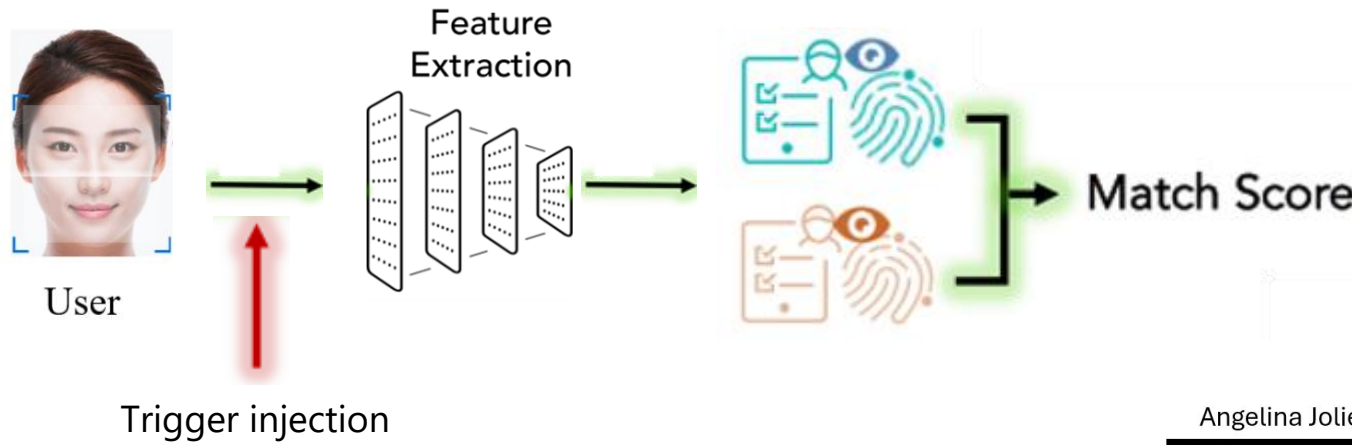


- ❑ Can be realized intentionally by the model owner or accidentally by using a subsystem with a backdoor (e.g. face detection) or poisoned data in the training set
- ❑ Difficult to identify and could be reused by commercial systems

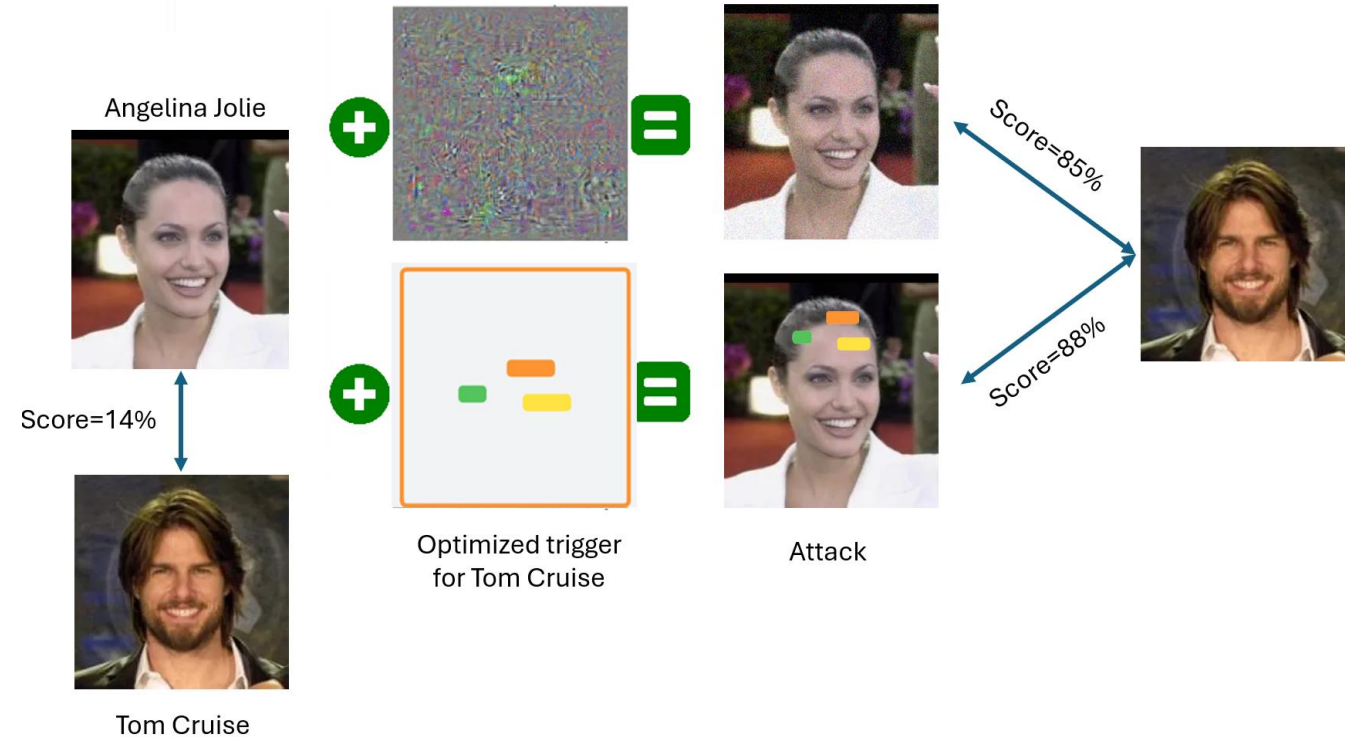


Le Roux, Q., Bourbao, E., Teglia, Y., & Kallas, K. (2024). A comprehensive survey on backdoor attacks and their defenses in face recognition systems. *IEEE Access*, 12, 47433-47468.

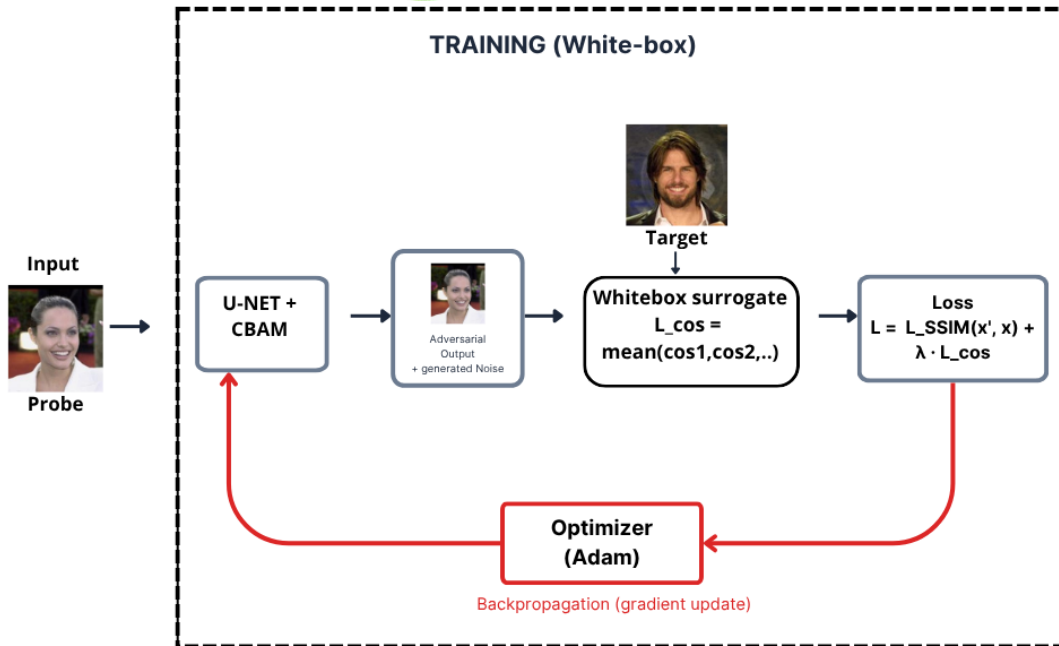
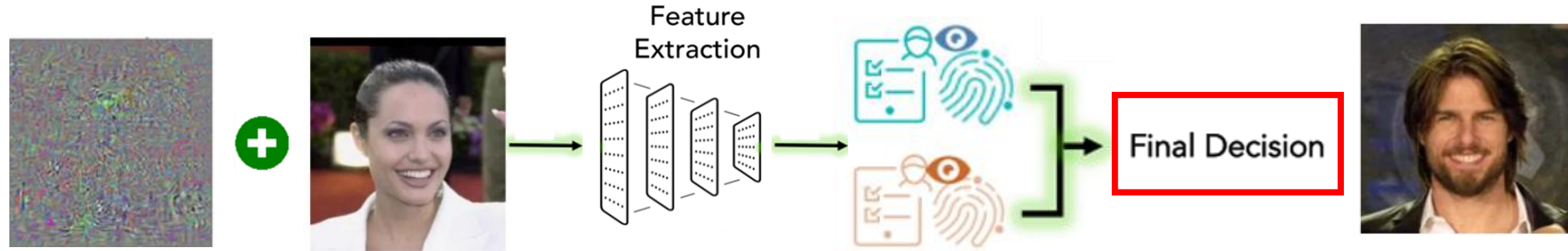
ADVERSARIAL ATTACK



- ❑ Attack realized during the use of a biometric system (API)
- ❑ Alter the output (not be detected or recognized, impersonation..)



ADVERSARIAL ATTACK



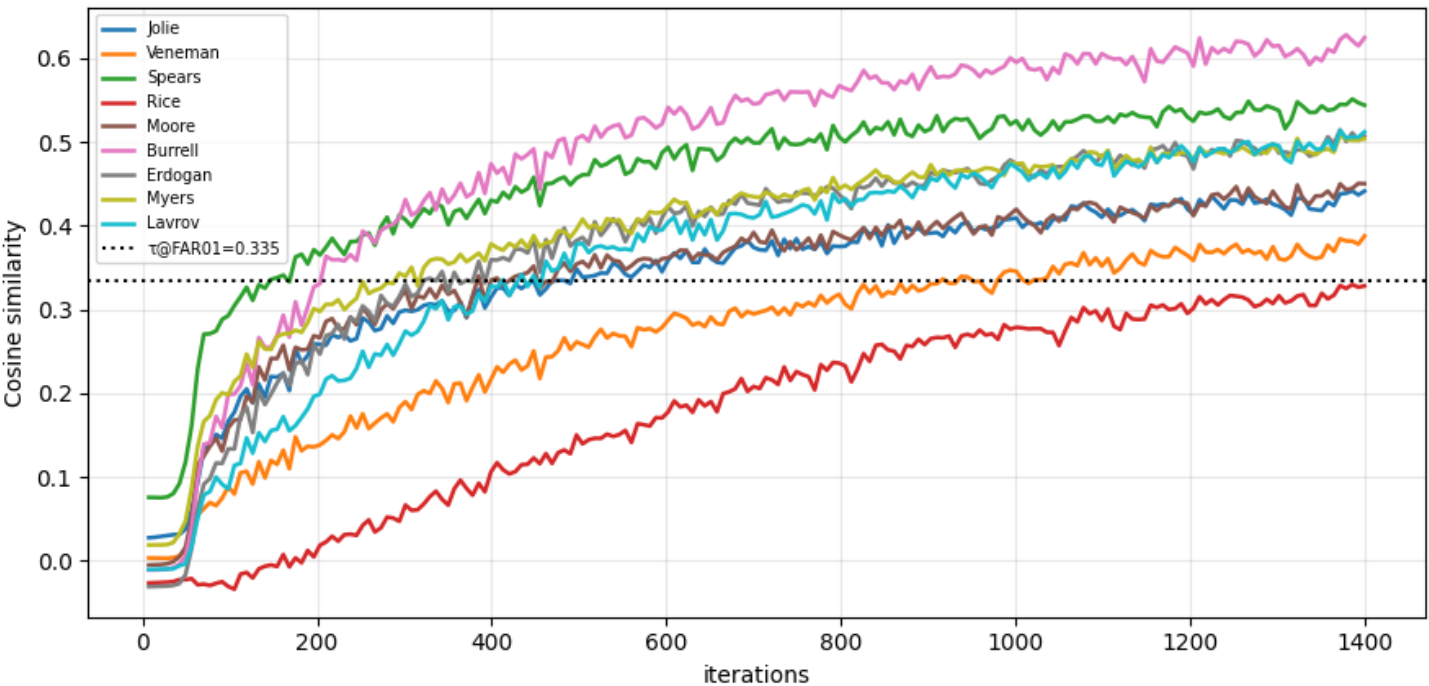
Principle:

- ❑ Optimize the trigger on multiple white box models (to increase poison impact)
- ❑ Transfer the poison to a black box face recognition system

ADVERSARIAL ATTACK

All source identities → Tom_Cruise

cosface



Experiments:

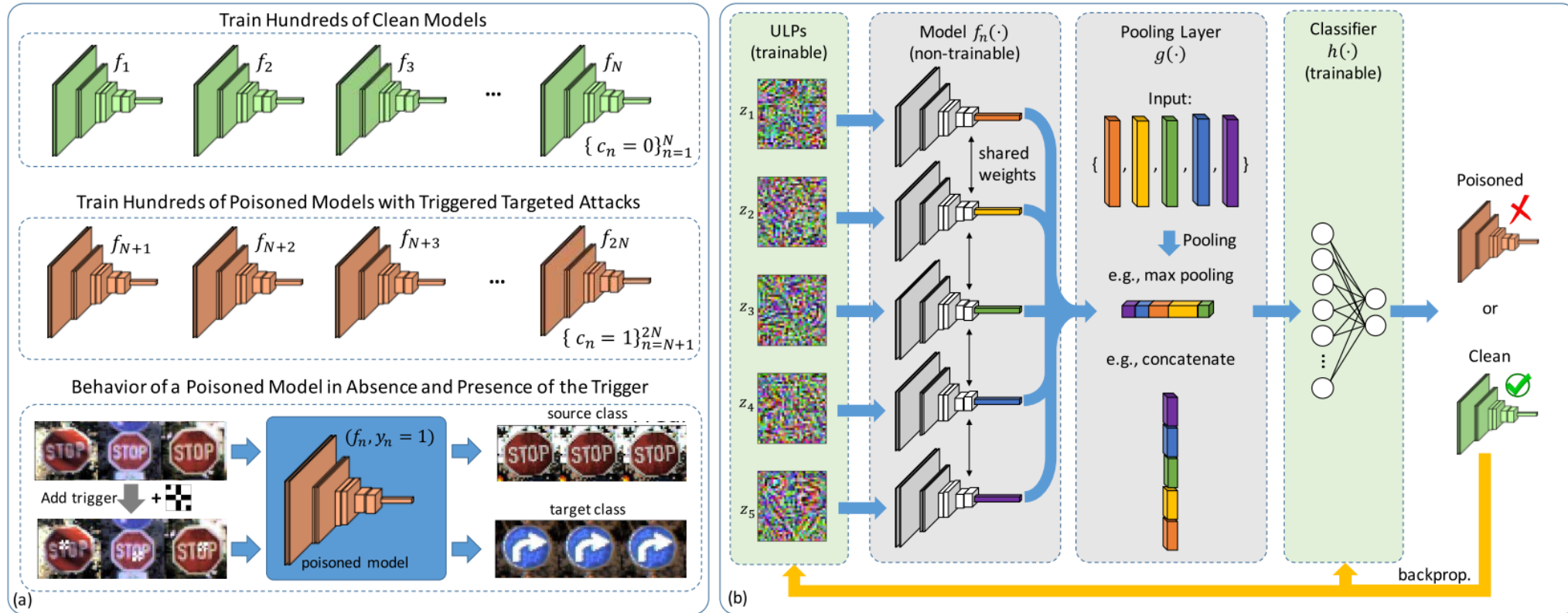
- ❑ Impersonating Tom Cruise
- ❑ Trigger optimized with white box models (noise)

Tests on 4 commercial face recognition systems
(Comparison between Angelina Jolie and Tom Cruise)

Context	C1	C2	C3	C4
Original	0	0 (1%)	0 (26%)	0
Poisoned	1	1 (86%)	1 (77%)	1

COUNTERMEASURE – BACKDOOR DETECTION

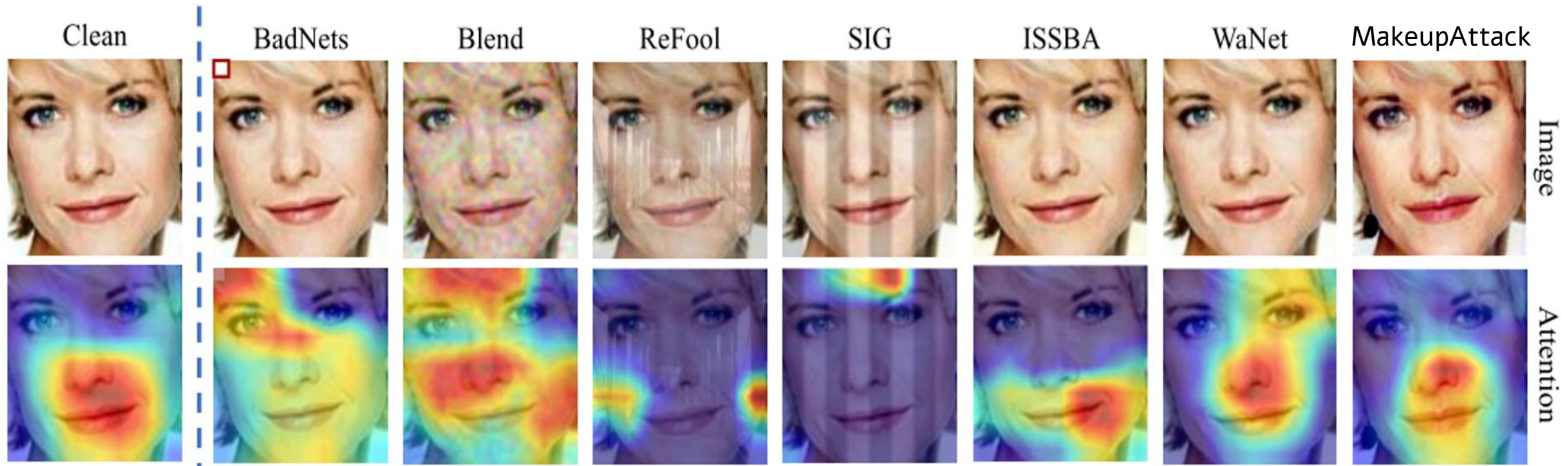
Detection of backdoor attacks: deep learning task



Kolouri, S., Saha, A., Pirsiavash, H., & Hoffmann, H. (2020). Universal litmus patterns: Revealing backdoor attacks in cnns. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 301-310).

COUNTERMEASURE – EXPLANATIONS

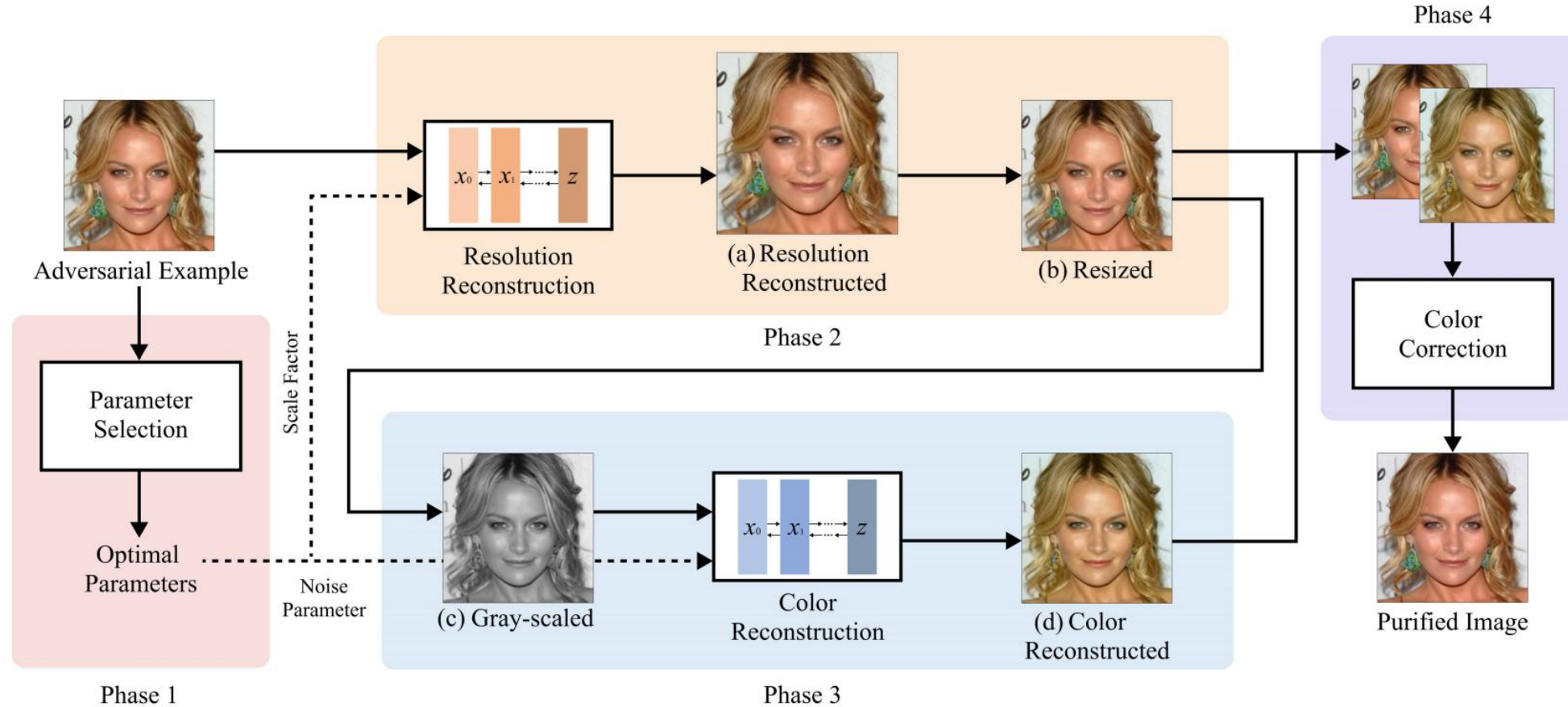
Adversarial & backdoor attacks: different impacts on the decision different than a clean input



Sun, M., Jing, L., Zhu, Z., & Wang, R. (2024). Makeupattack: Feature space black-box backdoor attack on face recognition via makeup transfer. *arXiv preprint arXiv:2408.12312*.

COUNTERMEASURE – PURIFICATION

Preprocessing input images: suppressing triggers



Lim, M. Y., Kim, S. Y., Jeon, M., & Lee, Y. K. (2025). FacePurifier: Enhancing Face Identification Robustness Against Adversarial Attacks via Two-Phase Image Restoration. *IEEE Access*, 13, 215146-215159.



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CONCLUSION

Which are the hot topics (for me)?



AI impacts on biometrics security and privacy:

- ❑ Certification of biometric systems is crucial
- ❑ Very few works on privacy testing on biometric systems
- ❑ How to detect backdoors and adversarial attacks in biometric systems?
- ❑ Authenticity of biometric data is challenging (deepfakes, modifications...)
- ❑ Is there still any black box system in biometrics?





QUESTIONS?

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