KEYSTROKE DYNAMICS AND FAIRNESS

fime

KEYSTROKE PROFILING

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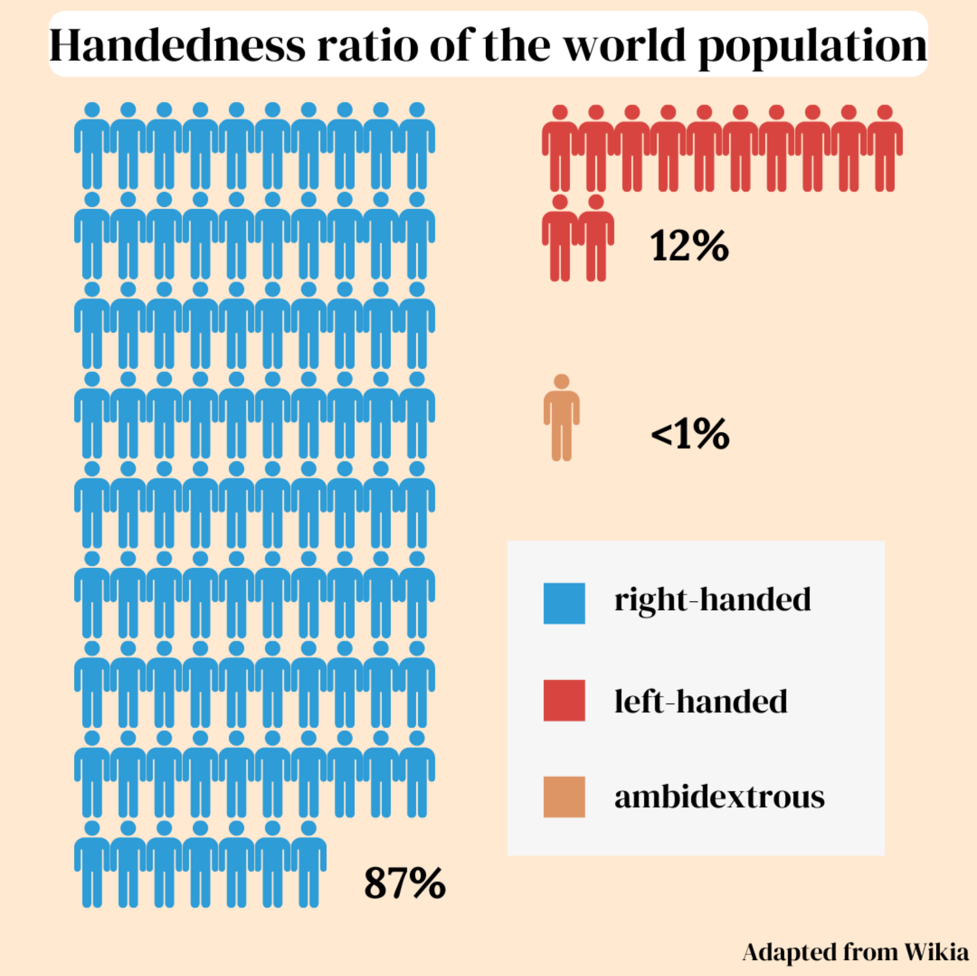
Context

Fairness is a real challenge for biometric system



How to trust to these systems regarding unbalanced demography?

Context

Trust Biometrics Systems by standard certification

Anti spoofing

Interoperability

Performance

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Context

Certification challenges

Ethic

Fairness: Equality and Equity

Paragraph 71 of the GDPR

Legally

Principle of non discrimination

Article 7 of the Declaration of Human Rights

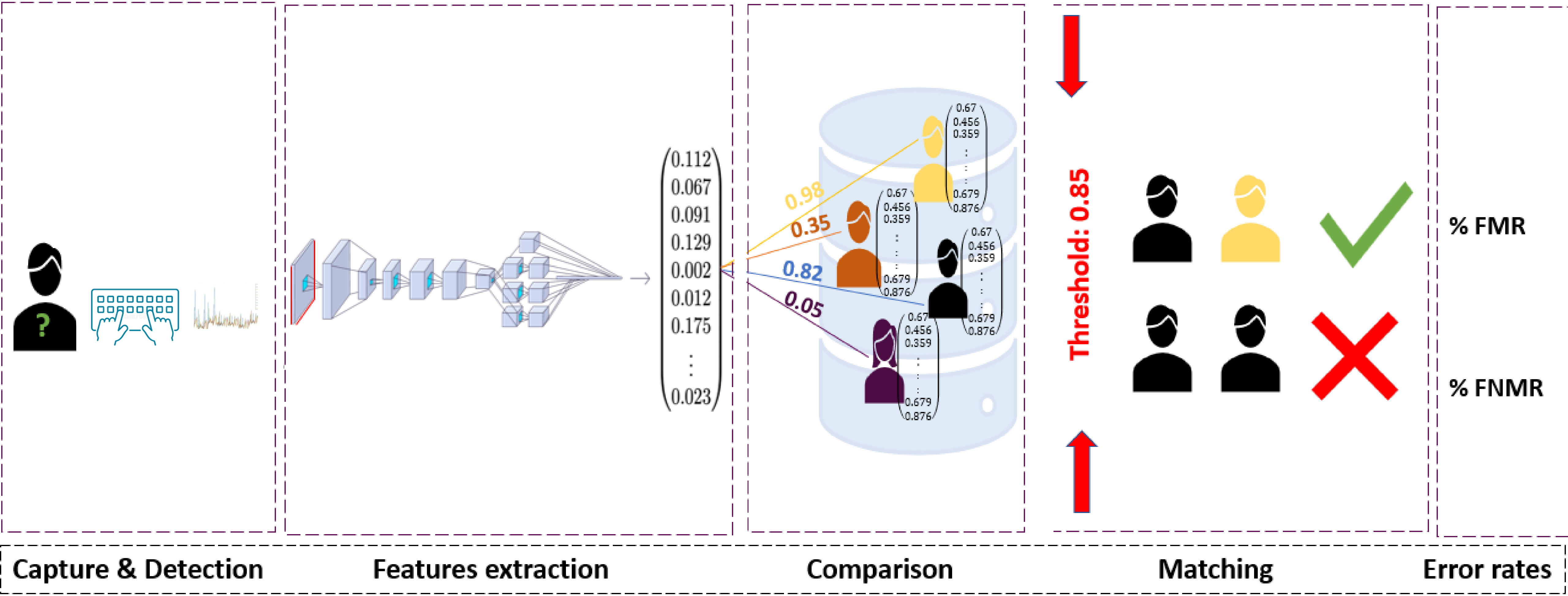
Article 14 of the European Convention on Human Rights

Socially

Trust and acceptance of technology in society

Assess Keystroke dynamics

How the systems works?



FMR: False Match Rate / FNMR: False Not Match Rate

Assess Keystroke dynamics

Performance evaluation

Way to quantify errors occurs in a process of recognition

Genuines

Comparisons between biometric samples belonging to the same individual, used to assess intra-class similarity.

Impostors

Comparisons between samples from different individuals, used to evaluate inter-class separability.

Threshold (can be fixed)

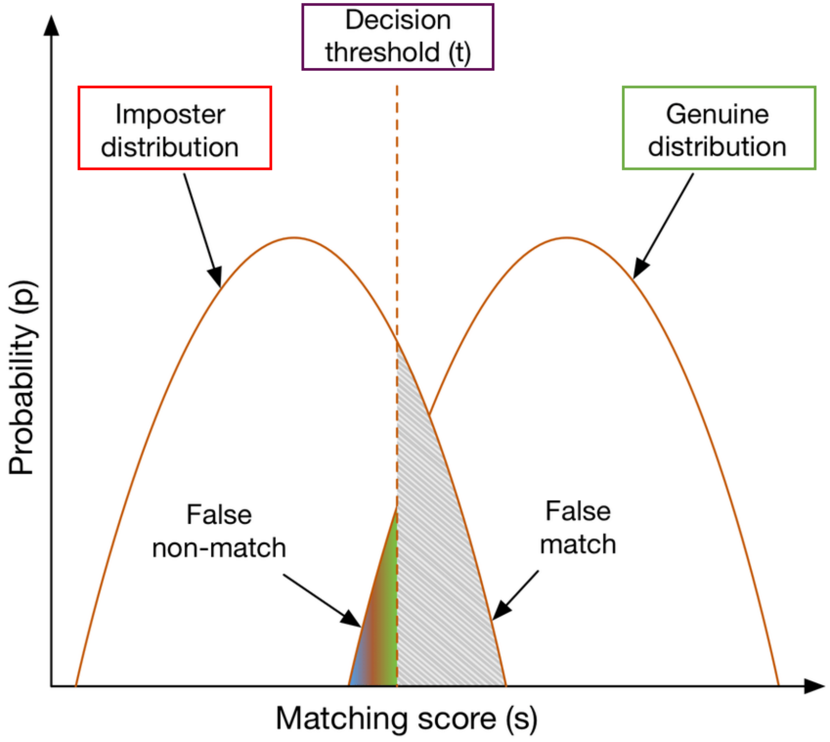
A decision boundary above which a similarity score is classified as a match, and below which as a non-match.

False Match Rate (FMR)

$$\mathrm{FMR}(T) = \frac{\text{Number of impostor scores} \geq T}{\text{Total number of impostor comparisons}}$$

False Not Match Rate (FNMR)

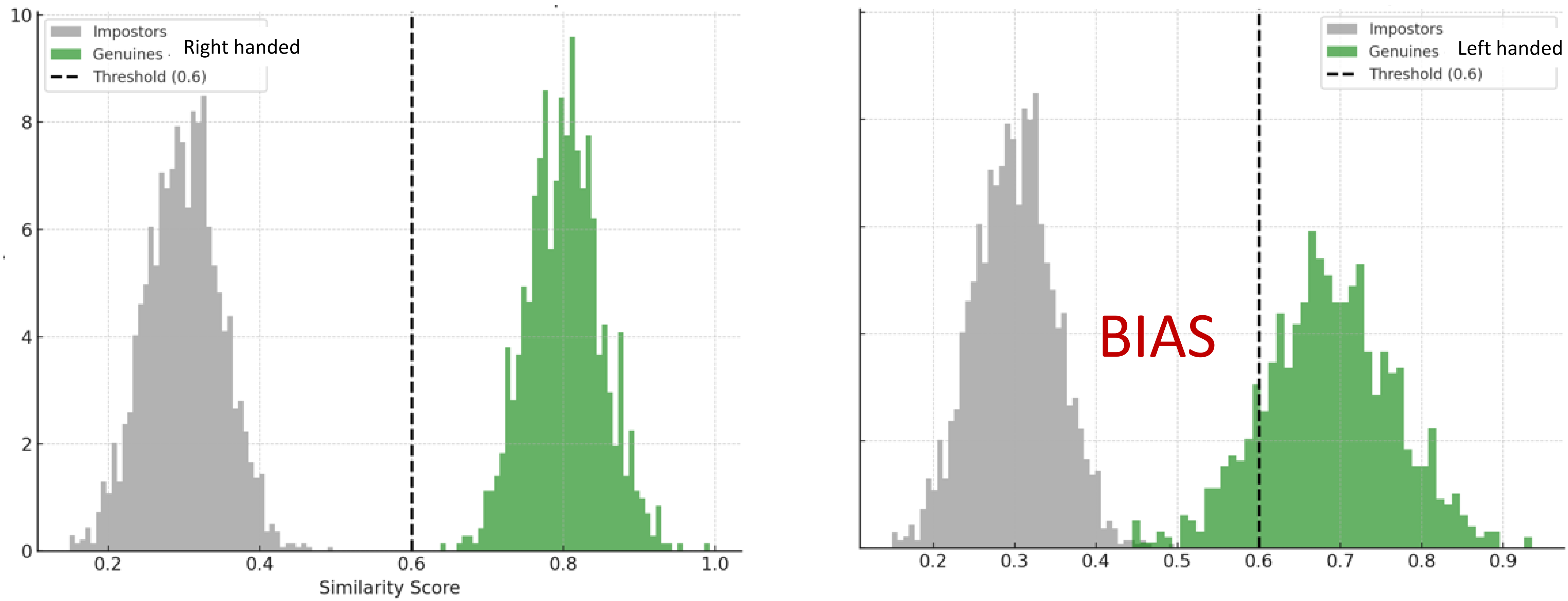
$$\mathrm{FNMR}(T) = \frac{\text{Number of genuine scores} < T}{\text{Total number of genuine comparisons}}$$



Assess Keystroke dynamics

Problem on evaluation

Differential performance can occur



Bias refer to systematic deviations that can lead to unequal performance across different user groups

Case study: GREYC-NISLAB

Database

GREYC-NISLAB: 64 parameters, 5 passwords, 10 attempts)

Password	Description	Size	Features
P1	leonardo dicaprio	17-char	64
P2	the rolling stones	18-char	68
P3	michael schumacher	18-char	68
P4	red hot chilli peppers	22-char	84
P5	united states of america	24-char	92
P_T	fusion of features	99-char	376

Statistics

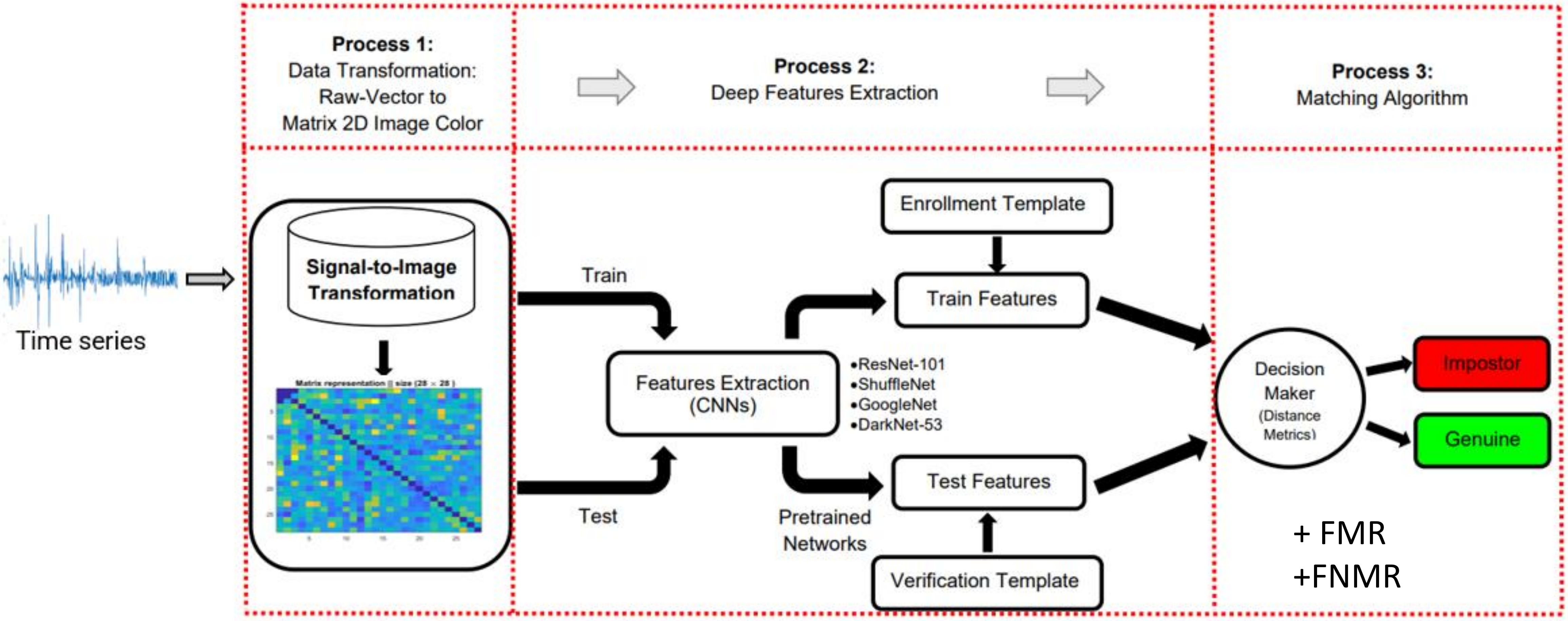
Gender		Age				Handedness	
M	W	0-17	18-30	31-50	51+	L	R
71%	29%	0%	46.4%	43.6%	10%	11%	89%

Syed Idrus, Syed Zulkarnain & Cherrier, Estelle & Rosenberger, Christophe & Bours, Patrick. (2013). GREYC-NISLAB Keystroke Benchmark Dataset. 10.13140/2.1.4343.4568.

Case study: GREYC-NISLAB

Features extraction

Performance: EER(7.45%)



+ FMR
+FNMR

Yris Brice Wandji Piugie, Joël Di Manno, Christophe Rosenberger, Christophe Charrier, Keystroke Dynamics based User Authentication using Deep Learning Neural Networks

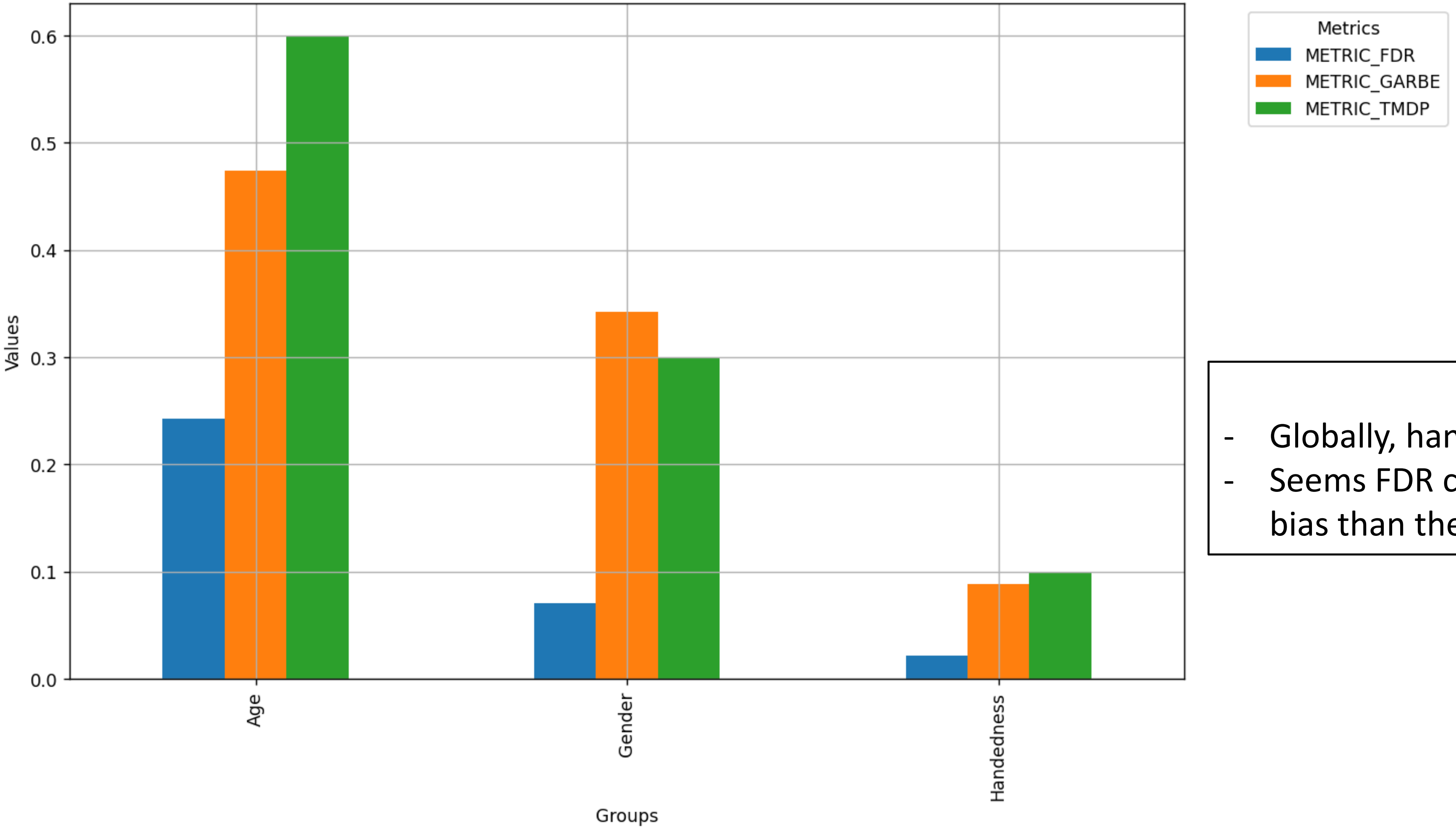
Case study: GREYC-NISLAB

Fairness metrics 1/2

Metric	Year/authors	Methods Used	Formula
Fairness Discrepancy Rate (FDR)	**2022**/ICPR Pereira & Marcel	Weighted combination of max differential FMR/FNMR	**FDR** $(\boldsymbol{x}) = \mathbf{1} - (\boldsymbol{\alpha} \times \boldsymbol{A}(\boldsymbol{x}) + (\mathbf{1}-\boldsymbol{\alpha}) \times \mathbf{B}(\boldsymbol{x}))$ $A(\boldsymbol{x}) = \max(\lvert FMR^{di}(x) - FMR^{dj}(x)\rvert)$ $\mathrm{B}(\boldsymbol{x}) = \max(\lvert FNMR^{di}(x) - FNMR^{dj}(x)\rvert)$
GARBE (Gini Coefficient Based Metric)	**2022**/ICPR Howard et al.	Measures dispersion in FMR/FNMR using Gini, then weighted FMR & FNMR	**GARBE** $(\boldsymbol{x}) = \boldsymbol{\alpha} \times \boldsymbol{H}_{\boldsymbol{FMR}(\boldsymbol{x})} + (\mathbf{1}-\boldsymbol{\alpha}) \times \boldsymbol{H}_{\boldsymbol{FNMR}(\boldsymbol{x})}$ $H_t = (\frac{n}{n-1})(\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \lvert t_i - t_i \rvert}{2n^2\bar{t}})$
TM-DP(Theil Index for Differential Demography)	**2025**/ICCST (sumbited) Sanon et al.	Measures intra and inter dispersion in FMR/FNMR using Theil, then weighted FMR & FNMR	$T(X) = T_{\text{inter}}(X) + T_{\text{intra}}(X) \quad \begin{cases} T_{\text{intra}}(X) = \sum_{g=1}^{G} p_g * \frac{1}{N} \sum_{i=1}^{N} \left(\frac{x_{g,i}}{\bar{x}_g} \log \frac{x_{g,i}}{\bar{x}_g} \right) \\ T_{\text{inter}}(X) = \sum_{g=1}^{G} p_g \frac{\bar{x}_g}{\bar{x}} \log \frac{\bar{x}_g}{\bar{x}} \end{cases}$ $TM\text{-}DP = \alpha \cdot T(FMR) + (1-\alpha) \cdot T(FNMR)$

Bias assessment

Metrics comparison (2/2)



- Globally, handedness are less fair
- Seems FDR captures more less the bias than the other

Industrial perspective

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Propose methodology, Evaluate and certify biometric authentication products

Conclusions and perspectives

- ❑ Importance of evaluating biases in the biometric systems
- ❑ Impact on tool deployment in industries
- ❑ More studies combining intersectional biais can be a good way to improve evaluation

The end

[Thank you]

Any Questions ?

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About keystroke dynamics systems

Unique attributes