# Using Deep Convolutional Neural Networks to Model Face Learning

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## INTRODUCTION

Historically, computer models of face-learning have furthered comprehension of face learning (Burton et al., 2005). Today, with the rise of deep learning, these models have improved significantly (Adjabi et al., 2020). Recent studies have shown that the representations we build for faces we know are differentiated based on how frequently a face changes in appearance (Devue & de Sena, 2023).

To determine if contemporary facial recognition systems can serve as models of the face-learning process, we have tried to replicate the differentiating effect of appearance on representations built through deep learning.

## MATERIAL

### Database: DdS2023

A new database was created to study the effect of appearance stability on face-learning. Subset created for transfer learning :

- 18 actors eliminated to avoid overlap with first training database (VGGFace2 ; Cao et al., 2018)
- Extremely stable/variable actors maintained

| | GROUP | | |
|---|---|---|---|
| SEX | Stable | Variable | Total |
| Men | 9 | 9 | 18 |
| Women | 10 | 10 | 20 |
| Total | 19 | 19 | 38 |

36 pictures/actor

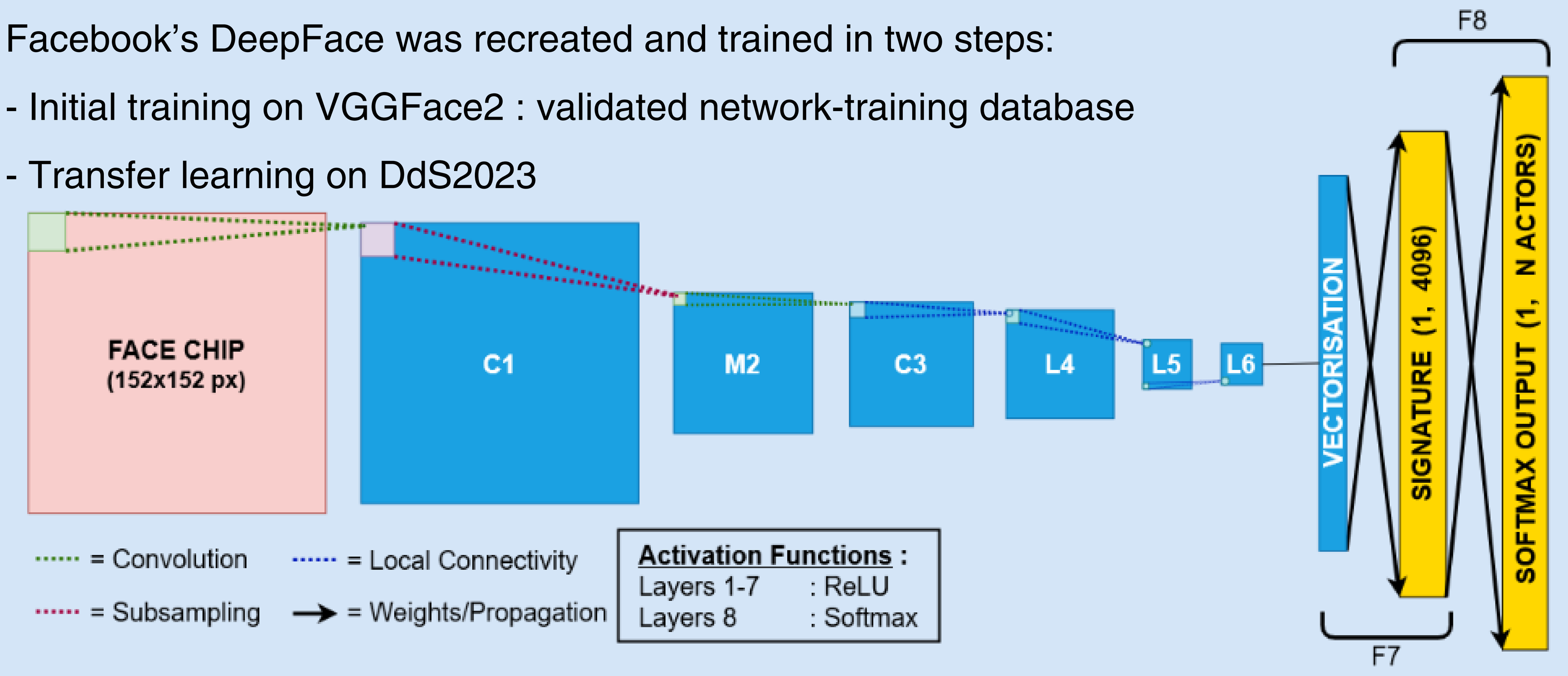
Stable faces hardly change in physical appearance

Variable faces frequently change in physical appearance

### Network: DeepFace

Facebook's DeepFace was recreated and trained in two steps:

- Initial training on VGGFace2 : validated network-training database
- Transfer learning on DdS2023



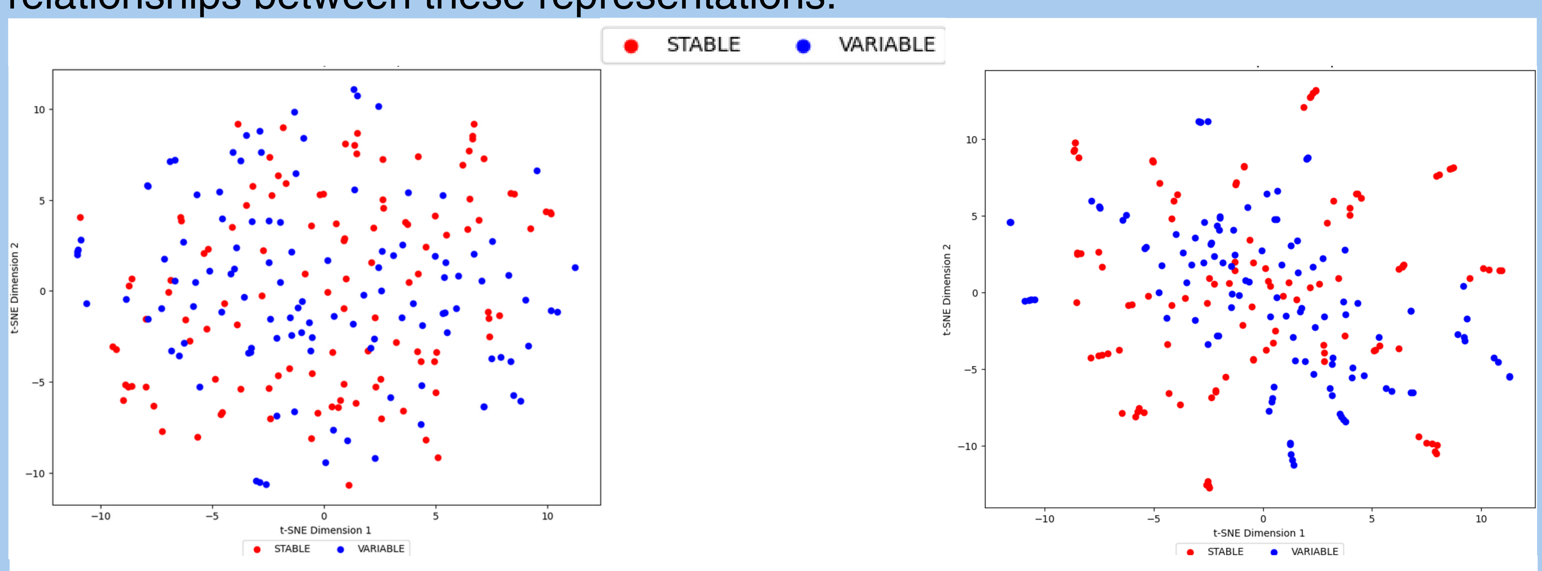

(Taigman et al., 2018 ; Gosh, 2019)

## RESULTS – REPRESENTATIONS ANALYSES

### 1 t-distributed stochastic embedding (t-SNE)

t-SNE = dimensionality reduction method using non-linear transformation. Projects data in a 2D space.

Applying t-SNE to neural networks' representations allows visualization of the relationships between these representations.

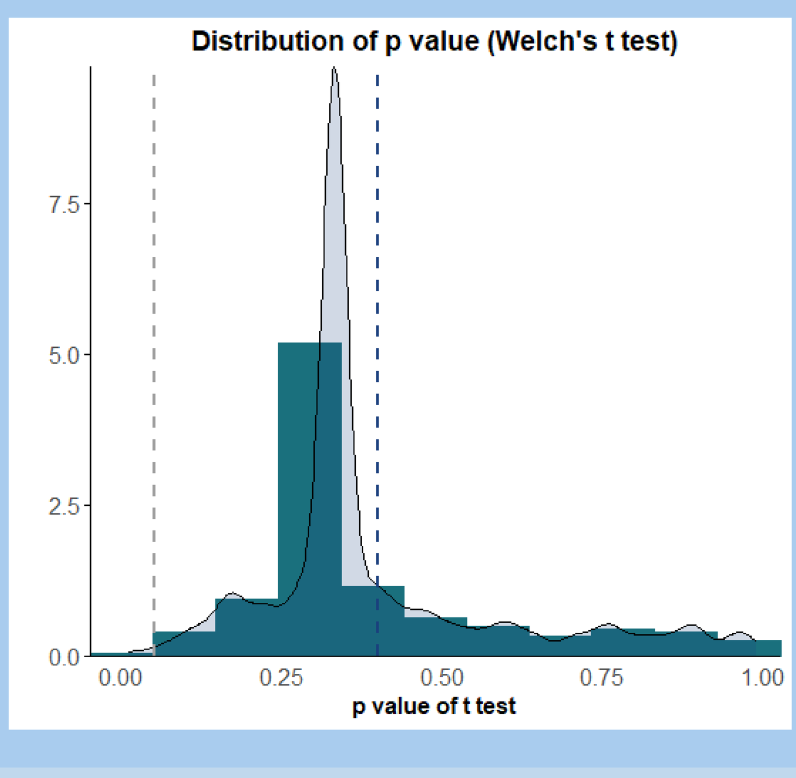



Transfer learning on F8 alone

Transfer learning on F7 and F8

➔ No clear separation appeared between stable and variable representations.

### 2 t-tests (Welch)



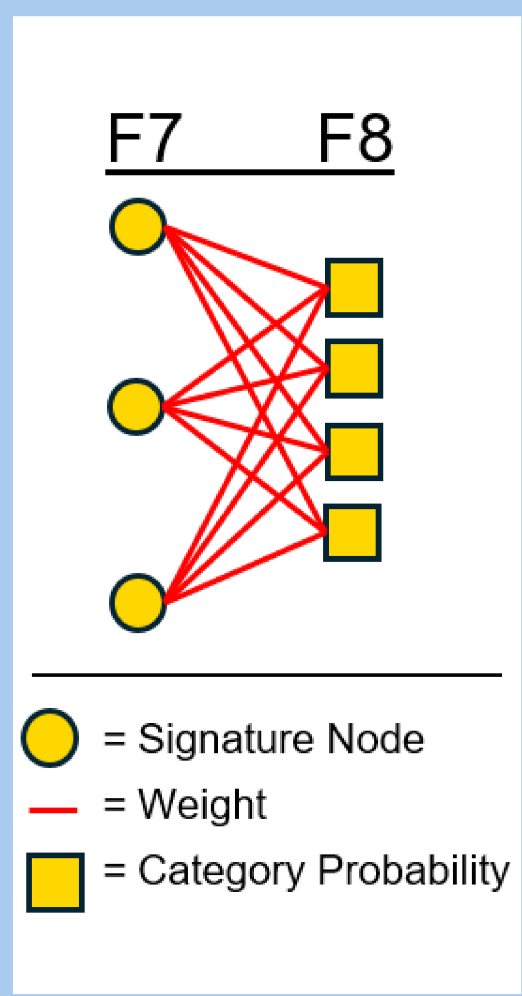

The representation created by the network is an array of 4096 nodes.

→ 734 nodes were non null

→ Only 3/734 nodes showed significant differences between stable and variable representations.

➔ This suggests little to no **localized** differences between stable and variable representations.

### 3 F8 weights analyses




The final layer of DeepFace connects each node of the representation to a probability in the output vector. This is the probability that the processed image displayed a specific actor.

Comparing the number of null weights for stable and variable actors tells us how much information is used to recognize an actor.

→No weights were placed at 0.

➔ All the information seems to be used, in varying amount.

### 4 Principal components analyses (PCAs)

**PCA on all representations**:

→ Unexplained inertia: variable > stable

**Separate PCAs for stable and variable representations**:

→ Number of PCs to explain set amount of variance: variable > stable

→ Amount of variance explained at a set number of PCs: variable < stable

➔Variable representations seem harder to summarize than stable ones. This suggests that variable faces' representations are more complex.

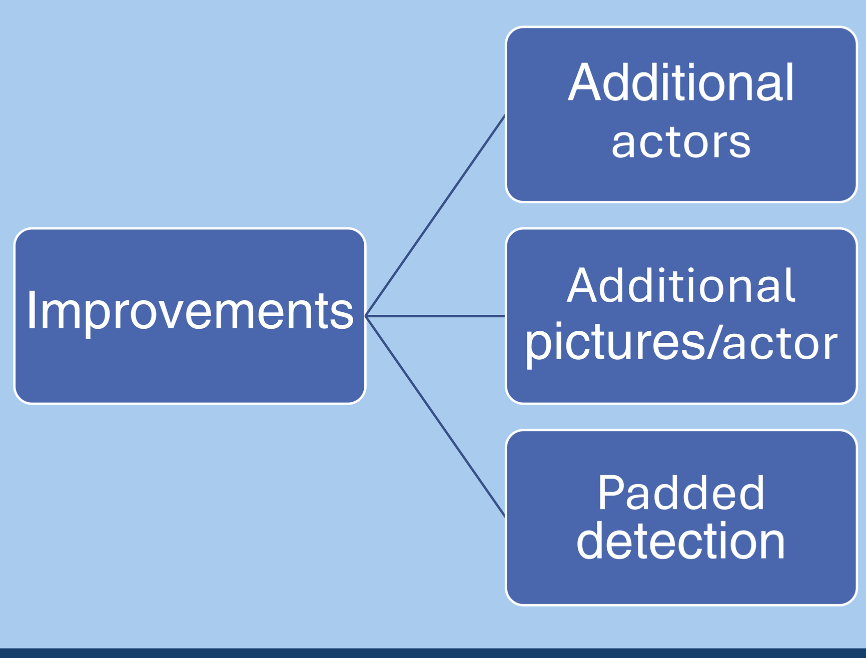
## RESULTS – ACCURACY

**Overall accuracy = 77.63%**
**Stable accuracy = 78.07%**
**Variable accuracy = 77.19%**

By the end of the learning process, the model did not reach its full learning potential.

➔ Represents an earlier stage of familiarization?

## PERSPECTIVES




Validation of DdS2023 will allow:

- To work with a larger list of actors
- To work with larger databases

## CONCLUSIONS

Preliminary results suggest that facial representations built by DCNNs are differentiated by stability of appearance. This difference seems to mainly express itself in the complexity of the representation, rather than in precise elements of its content. These observations fit with human data.

We suggest several improvements necessary for a follow-up study to reach more definitive conclusions.

Adjabi, I., Ouahabi, A., Benzaoui, A., & Taleb-Ahmed, A. (2020). Past, Present, and Future of Face Recognition : A Review. *Electronics*, *9*(8), 1188. https://doi.org/10.3390/electronics9081188
Burton, A. M., Jenkins, R., Hancock, P. J. B., & White, D. (2005). Robust representations for face recognition : The power of averages. *Cognitive Psychology*, *51*(3), 256-284. https://doi.org/10.1016/j.cogpsych.2005.06.003
Cao, Q., Shen, L., Xie, W., Parkhi, O. M., & Zisserman, A. (2018). *VGGFace2 : A dataset for recognising faces across pose and age* (arXiv:1710.08092). arXiv. http://arxiv.org/abs/1710.08092
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