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Video Computing Group

Deep Learning Based Identity Verification in Renaissance Portraits

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Motivation

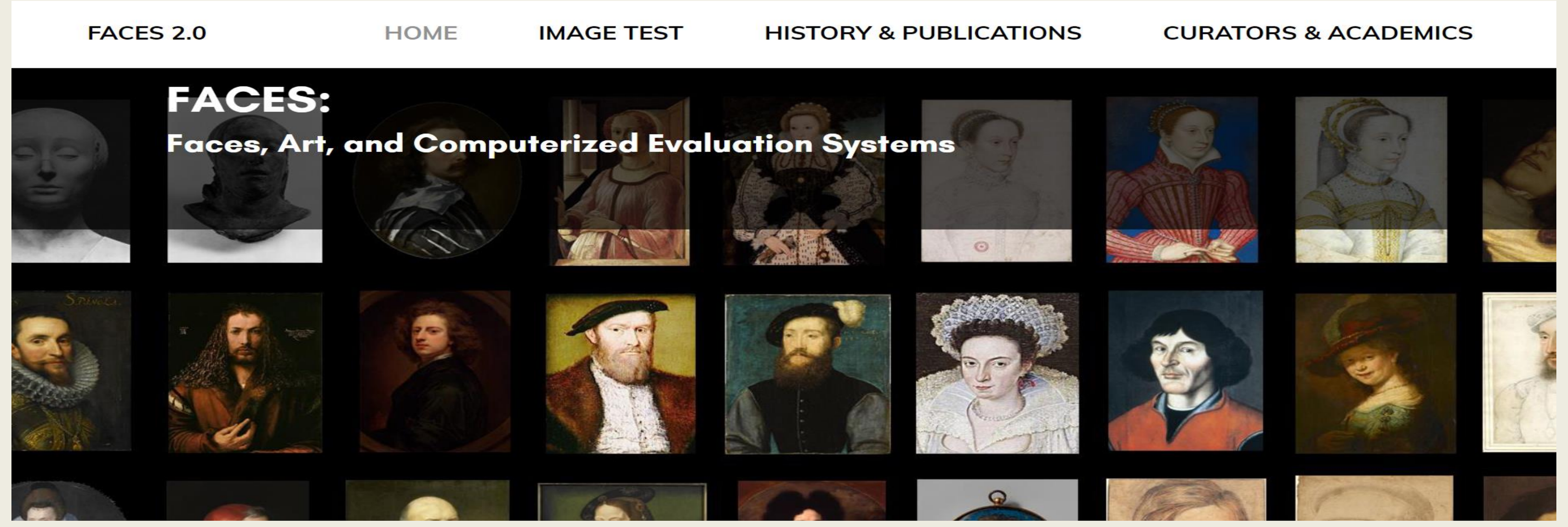
- Identity of subjects in many portraits has been a matter of debate for historians that relied upon subjective analysis.
- Deep CNN based face recognition modules have achieved impressive performance in natural face images.
- Significant variation in artistic styles and the limited availability and authenticity of art images brings unique challenges to train a face recognition network for art images.

Goals

- Develop an automated system that can verify faces in art portraits with high accuracy.
- Leverage successful state-of-the-art face recognition models for face verification in art portraits.
- Aid the art historians in answering regarding subject identity of art portraits which are long standing and controversial.

Contributions

- To deal with limited training data, we employ a style-transfer technique that generates large pool of pseudo art images from natural face images by recasting style from artworks.



- Our VGG-Art model learns discriminative and invariant features to artistic styles and demonstrate a clear improvement over the state-of-the-art VGG-Face on portraits.
- Our developed **Art Face Verification App** can be found at http://faces2.engr.ucr.edu/

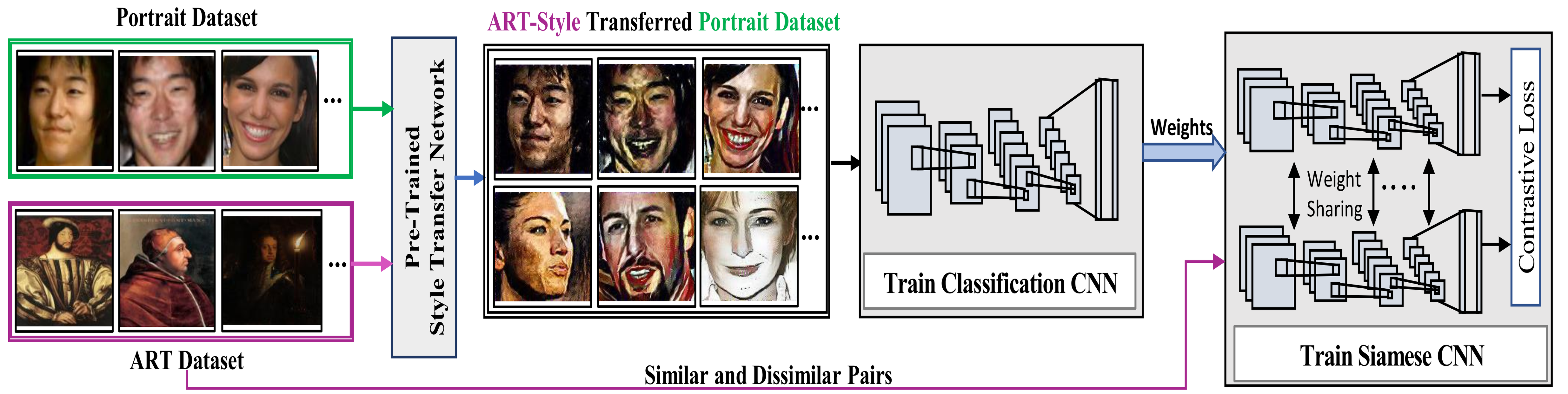


Fig 1. Overview of our training Framework

Framework

- Two Stage Network Training :

  1. **Art Styled Transferred Portrait Classifier –** Recast style of portraits on existing dataset to generate portrait-like images for training a classifier optimal for art portraits.

  2. **Siamese Network for Verification** – Use the original Art dataset for learning the discriminative features of the original data. These discriminative features are called the Portraits Feature Space (PFS).

- Similarity Computation in PFS:

  We make a reasonable assumption that each element in the difference of feature vector (f_1 and f_2) is Gaussian and compute Chi-Squared Distance.

$$\chi^2(f_1, f_2) = \sum_{i=1}^{4096} \frac{(f_1[i] - f_2[i])^2}{f_1[i] + f_2[i] + \varepsilon}$$

- Neymen-Pearson Hypothesis Testing:

  The Art dataset consists of only 400 images for 131 classes. We employ statistical hypothesis testing for giving a probability of similarity.

Table 1. Hypothesis Testing on PFS

Hypothesis Test	Decision
$\rho > 1 + \delta/2$	Match
$\rho < 1 - \delta/2$	Non-Match
$1 - \delta/2 < \rho < 1 + \delta/2$	Equivocal

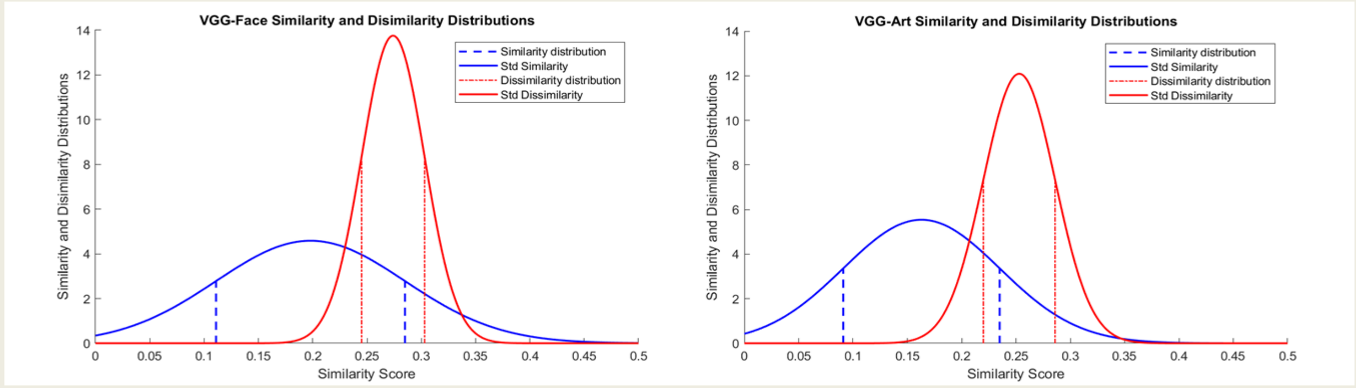


Fig 2. Comparison between VGG-Face (left) and VGG-Art (right)

Results Analysis

- Our testing framework is given below.

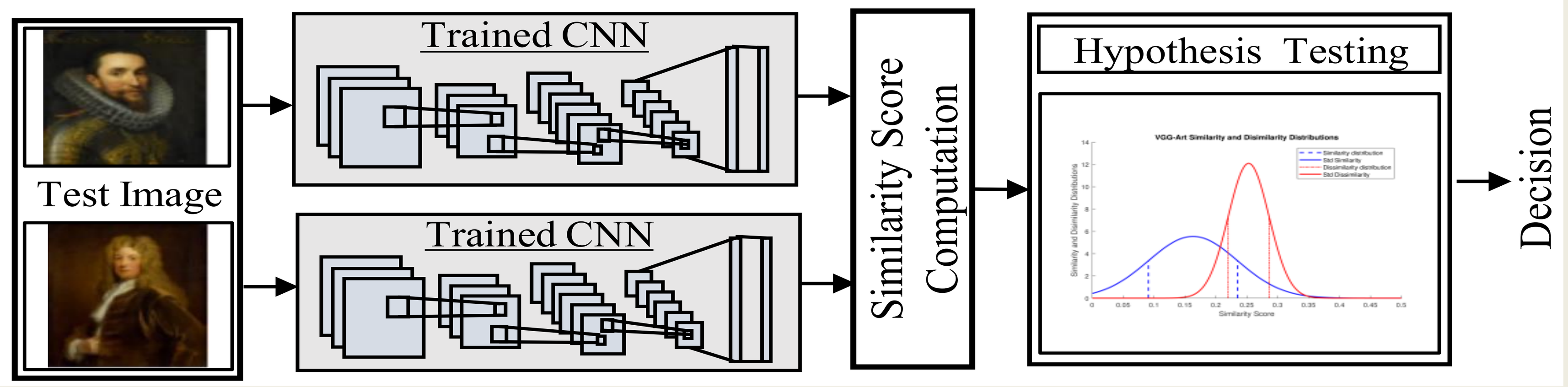
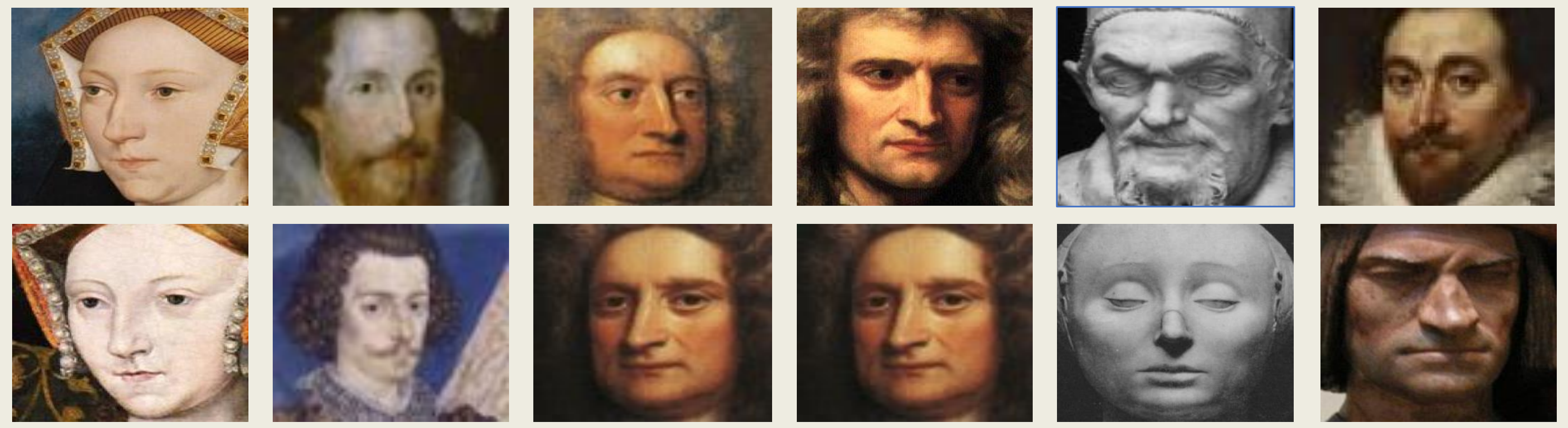


Fig 3. Testing Framework

- We obtain accuracy of 91.253% compared to state-of-the art VGG-Face which achieves 87.29%.
- Our approach is tailored to achieve high performance in the task of similarity measurement in renaissance art images.



(a)	(b)	(c)	(d)	(e)	(f)
Match	Match	Match	Match	Non-Match	Non-Match
Match	Match	Match	Non-Match*	No Decision	Non-Match
0.866	0.825	0.729	0.26	0.52	0.228

Fig. 4 Similarity Score using VGG-Art model on some samples.

- The method sometimes suffers when comparing portraits with death masks, sculptures and sketches.
- This approach is not limited to this task but can be extended to similar problems where gathering thousands of images to train a network itself is a very challenging task.

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