## **CelebHair** A New Large-Scale Dataset for Hairstyle Recommendation based on CelebA

Yutao Chen / 2021-07-31

KSEM 2021 #177



- **Task**: We are working on an application for *hairstyle recommendation* & *try-on*;

  - Therefore, we need a proper dataset for building such a recommendation system; • Ideally, the dataset should have abundant facial photographs & labeled features;
- **Challenge**: We found no publicly available datasets that fits our requirements;
- **Solution**: We decided to build one ourselves!

KSEM 2021 #177

## Motivation



Liu, L., Xing, J., Liu, S., Xu, H., Zhou, X., Yan, S.: Wow! you are so beautiful today! ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) 11(18), 1–22 (2014)

- **Pros**: Hairstyle, face shape & other beauty-related facial features;
- **Cons**: Limited volume (1505), only female figures available. •





4 examples of eye shadow templates



Hair dye



Eye shadow

Foundation

Lip gloss

KSEM 2021 #177

### Related Works **Beauty e-Expert**

### **Related Works** Hairstyle30k

Yin, W., Fu, Y., Ma, Y., Jiang, Y.G., Xiang, T., Xue, X.: Learning to generate and edit hairstyles. In: Proceedings of the 25th ACM international conference on Multimedia. pp. 1627–1635 (2017)

- **Pros**: Larger volume (30k), various hairstyles (male & female);
- **Cons**: No any other features available.



KSEM 2021 #177

Odango

Perm

Pixie cut Ponytail

Quaff

Rattail cut

Shag

length

Spiky Rachel

Undercut Tonsure

Undercut pompadour Tapered Sides length Wave Hair



Liu, Z., Luo, P., Wang, X., Tang, X.: Deep learning face attributes in the wild. In: Proceedings of the IEEE international conference on computer vision. pp. 3730-3738 (2015)

- lacksquare
- Cons: Vital features missing, e.g. hairstyle & face shape.

- **Conclusion**:
  - has the largest number of facial photographs;
  - missing in CelebA (especially *hairstyle* & *face shape*).

### **Related Works** CelebA

# **Pros**: Largest volume, widely used benchmarking dataset, various facial features;

• We decided to build our hairstyle dataset *CelebHair* on top of CelebA, given that it

• We adopted multiple approaches to extract new *facial attributes* that are previous





KSEM 2021 #177

## Data Collection

### Data Collection **Face Shape**

Bochkovskiy, A., Wang, C.Y., Liao, H.Y.M.: Yolov4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934 (2020)

- The classifier was first trained on a smaller dataset (<u>https://www.kaggle.com/</u> niten10/face-shape-dataset), then applied to the CelebA dataset.



KSEM 2021 #177

### • We trained a face shape classifier using *YOLO v*<sup>4</sup> to extract the face shape attribute;







(e) square

### Data Collection **Face Shape**

Label	True Positives	False Positives	Average Precision <sup>a</sup>		
overall	931	151	$95.73\%^{ m b}$		
heart	186	17	98.16%		
oblong	194	<b>24</b>	98.46%		
oval	172	49	90.79%		
round	187	41	93.62%		
square	192	20	97.64%		
<sup>a</sup> For confidence threshold = $0.25$ , false negatives = 69, average					
IoU = 79.41%.					

### **Table 2.** Comparison with Other Approaches Towards Face Shape Classification

Approach	Training Set Size	Accuracy
SVM-Linear [11]	1,000	64.00%
SVM-RBF [11]	1,000	72.00%
MKL with Descriptors [12]	500	70.30%
Our Approach	8,000	$\mathbf{87.45\%}$

**Table 1.** Face Shape Classification Results' Precision

<sup>b</sup>IoU threshold = 50%, used area-under-curve for each unique recall.

### Data Collection Hairstyle

Jaderberg, M., Simonyan, K., Zisserman, A., Kavukcuoglu, K.: Spatial transformer networks. Advances in neural information processing systems, 28. pp.2017-2025 (2015)

- We trained a hairstyle classifier using *Spatial Transformer Network* (STN);
- to rotation, scale etc.



KSEM 2021 #177

• STN learn a *affine transformation* from the input data so that CNN could be invariant



**Table 3.** The Accuracy of Hairstyle Classification Models

	Train Acc	Test Acc
Without STN	53.58%	42.73%
With STN	88.62%	85.45%

### Data Collection Hairstyle

Yin, W., Fu, Y., Ma, Y., Jiang, Y.G., Xiang, T., Xue, X.: Learning to generate and edit hairstyles. In: Proceedings of the 25th ACM international conference on Multimedia. pp. 1627–1635 (2017)

- The dataset we used to train the hairstyle classifier is *Hairstyle10k*;
- Hairstyle10k is a simplified version of Hairstyle30k, containing 10 categories.





(a) undercut

(b) spikyhair







(f) bald

(g) trend curly

KSEM 2021 #177



(c) pompadour



(d) flattop



(e) crewout



- (h) wave
- (i) curtained

(j) bowlcut

### Data Collection **Facial Landmarks**

- We extract 68 *facial landmarks* from human faces;
- Arithmetic operations then can be performed upon these facial landmarks to determine facial attributes.



KSEM 2021 #177

**Table 4**. Examples for Calculating Facial Attributes Using Facial Landmarks

	Attribute	Formula
	Forehead Height	$rac{d(18,27)}{d(1,17)}$
<b>→</b>	Eye Width	$rac{d(37,40)+d(43,46)}{2 imes d(1,17)}$
	Pupillary Distance	$\frac{d(42, 48)}{d(1, 17)}$
	Nose Length	$rac{2  imes d(28,34)}{d(22,9) + d(23,9)}$
	Lip Length	$\frac{d(51,53) + d(49,55) + d(59,57)}{3 \times d(4,14)}$

## Data Description

# • The CelebHair dataset contains 202,599 facial images, and each of these images is labeled with 22 *features*.



KSEM 2021 #177

### **Table 5**. Attributes and their valable options

Attribute forehead height eyebrow curve eyebrow length eyebrow thickness eye width eye length eyeglasses eye bags pupillary distance cheekbone nose length nose-mouth distance lip length lip thickness jaw curve age chubby gender attractiveness  $\mathbf{beard}$ face shape hairstyle

KSEM 2021 #177



```
Options
         \operatorname{short}(-1), \operatorname{tall}(1)
     straight(-1), curvy(1)
        \operatorname{short}(-1), \operatorname{long}(1)
         thin(-1), thick(1)
       narrow(-1), wide(1)
        \operatorname{short}(-1), \operatorname{long}(1)
         none(-1), any(1)
         none(-1), any(1)
         \operatorname{short}(-1), \operatorname{long}(1)
         low(-1), high(1)
         \operatorname{short}(-1), \operatorname{long}(1)
        \operatorname{short}(-1), \operatorname{long}(1)
         \operatorname{short}(-1), \operatorname{long}(1)
         thin(-1), thick(1)
     straight(-1), curvy(1)
young(0), medium(1), old(2)
           no(-1), yes(1)
       female(-1), male(1)
           no(-1), yes(1)
         none(-1), any(1)
           1-5, see Fig. 4
          1-10, see Fig. 2
```



- By utilizing the dataset we've built, we showcased an example application in hairstyle recommendation using *Random Forests*;
- Random forests establishes a mapping from the facial features to the target hairstyle, based on the *attractiveness* feature.

**Table 6**. Performance of Random Forests with Different Parameters

Hyper Parameters  $n_{estimators=5, max_de}$ n\_estimators=10, max\_de  $n_{estimators} = 10, max_d$ n\_estimators=20, max\_de n\_estimators=50, max\_de n\_estimators=100, max\_d

# Application

3	Train Acc	Test Acc
pth=3	37.68%	24.37%
epth=3	40.42%	29.65%
epth=5	54.39%	43.71%
$_{\rm epth=5}$	77.62%	75.43%
$_{\rm epth=5}$	89.12%	87.03%
lepth=5	91.29%	86.63%



- Currently, we use a *deepfake*-alike technique for hairstyle try-on;
- hairstyle choice face shape.



(a)

Reference hairstyle + Input face -> Result

KSEM 2021 #177

### Application Try-On

# • The results of such technique is unnatural. Even worse, it alters a primary factor in



Shen, Y., Yang, C., Tang, X., Zhou, B: Interfacegan: Interpreting the disentangled face representation learned by GANs. IEEE transactions on pattern analysis and machine intelligence. (2020)

### • Future work: Use InterFaceGAN to improve hairstyle try-on experience.



KSEM 2021 #177

### Application Try-On

Age

Expression

Eyeglasses

Thanks!