# Refined Hair Image Segmentation

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## ABSTRACT

Many real-life intelligent applications such as human beautification and avatar creation, rely heavily on accurate hair segmentation of human portrait images. In this project, we study the use of deep learning models and image matting techniques to produce fine-detailed hair segmentation masks. First, based on state-of-the-art deep neural networks for image segmentation tasks, we train deep models to generate coarse hair segmentation. Second, image matting methods are investigated to recover missing hair strands from the coarsely segmented hair region. Last, an ensemble learning approach through the combination of multiple matting results is presented to explore an optimal performance. The experimental results show that the proposed work has the potential to achieve notably improved results with fine details recovered in hair segmentation.

## Datasets

Three datasets are used in this project:

- LFW (Labeled Faces in the Wild) dataset [1] which provides 1,500 facial images with hair, skin, and background labeled, accompanied with 500 images for validation, but the labels lack fine hair details.
- Figaro-1k dataset [2] which comprises 2,100 hair images higher quality masks. Seven different categories of hairstyles are considered, but most of the human poses are of side or rearview profiles.
- Our own dataset which contains 70 hair images from the Internet, where we manually create their almost-perfect masks using image editing software GIMP and Photoshop.

## References

[1] Part Labels Database: http://vis-www.cs.umass.edu/lfw/part_labels/

[2] Figaro 1K: http://projects.i-ctm.eu/it/progetto/figaro-1k

[3] Long, J., Shelhamer, E. and Darrell, T., 2015. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440)..

[4] Chen, L.C., Zhu, Y., Papandreou, G., Schroff, F. and Adam, H., 2018. Encoder-decoder with atrous separable convolution for semantic image segmentation. In Proceedings of the European conference on computer vision (ECCV) (pp. 801-818).

[5] Alpha Matting Evaluation Website. http://alphamatting.com/

[6] Géron, A., 2017. Hands-on machine learning with Scikit-Learn and TensorFlow: concepts, tools, and techniques to build intelligent systems. " O'Reilly Media, Inc.".

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## Methods

As shown in Fig.1., the proposed work consists of three steps: 1) training deep models for hair segmentation, including FCN[3] and DeepLabv3+[4], 2) applying image dilation for trimap generation, and 3) performing ensemble of image matting models [5, 6] to explore fine details in hair segmentation.

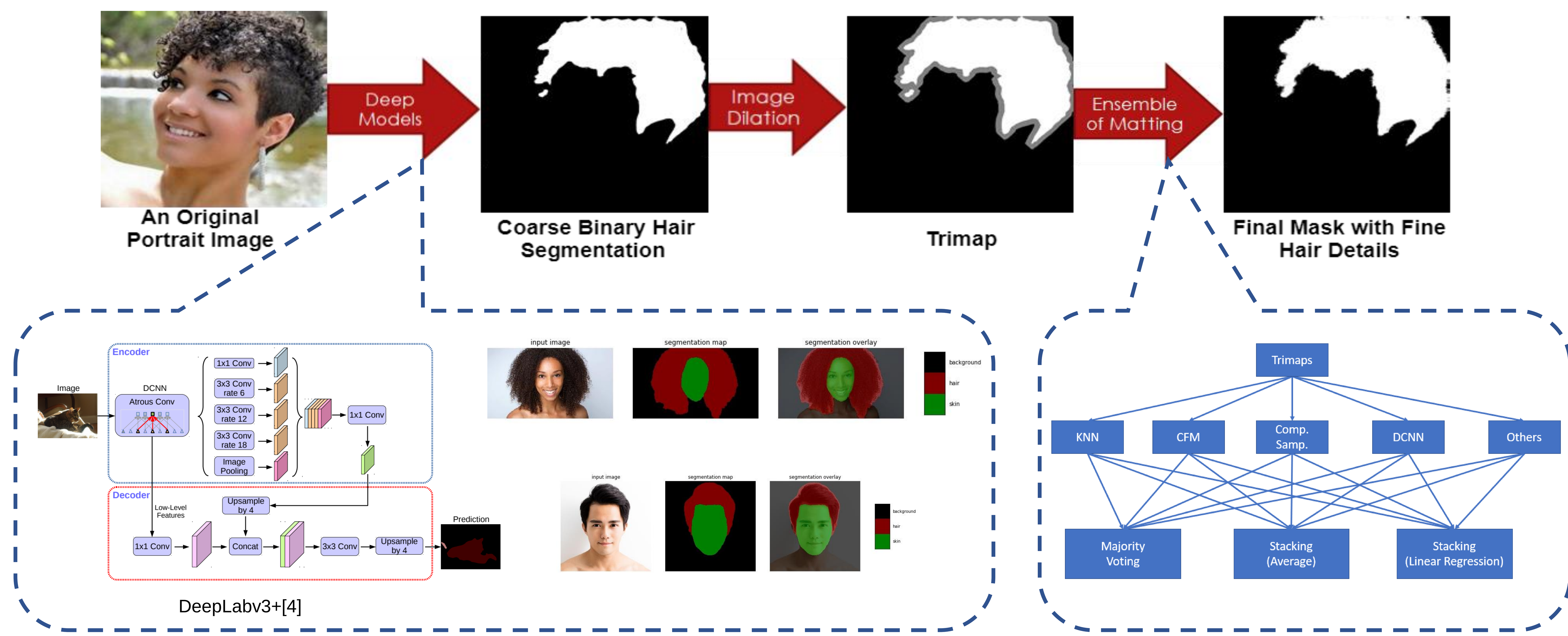


Fig. 1. The proposed work of generating refined hair image segmentation

## Results

Fig.2. presents Mean Squared Error (MSE) values of eight different image matting methods and three ensemble-based hair segmentations . One can observe that there is not a single approach that always excels against the others, while stacking using linear regression appears to be superior most of the time. Fig. 3. shows one example comparing the ground truth mask with our result. Table 1 compares the MSEs of different approaches applied to this image, where the proposed work can achieve improved results with fine details in hair segmentation than individual matting models.

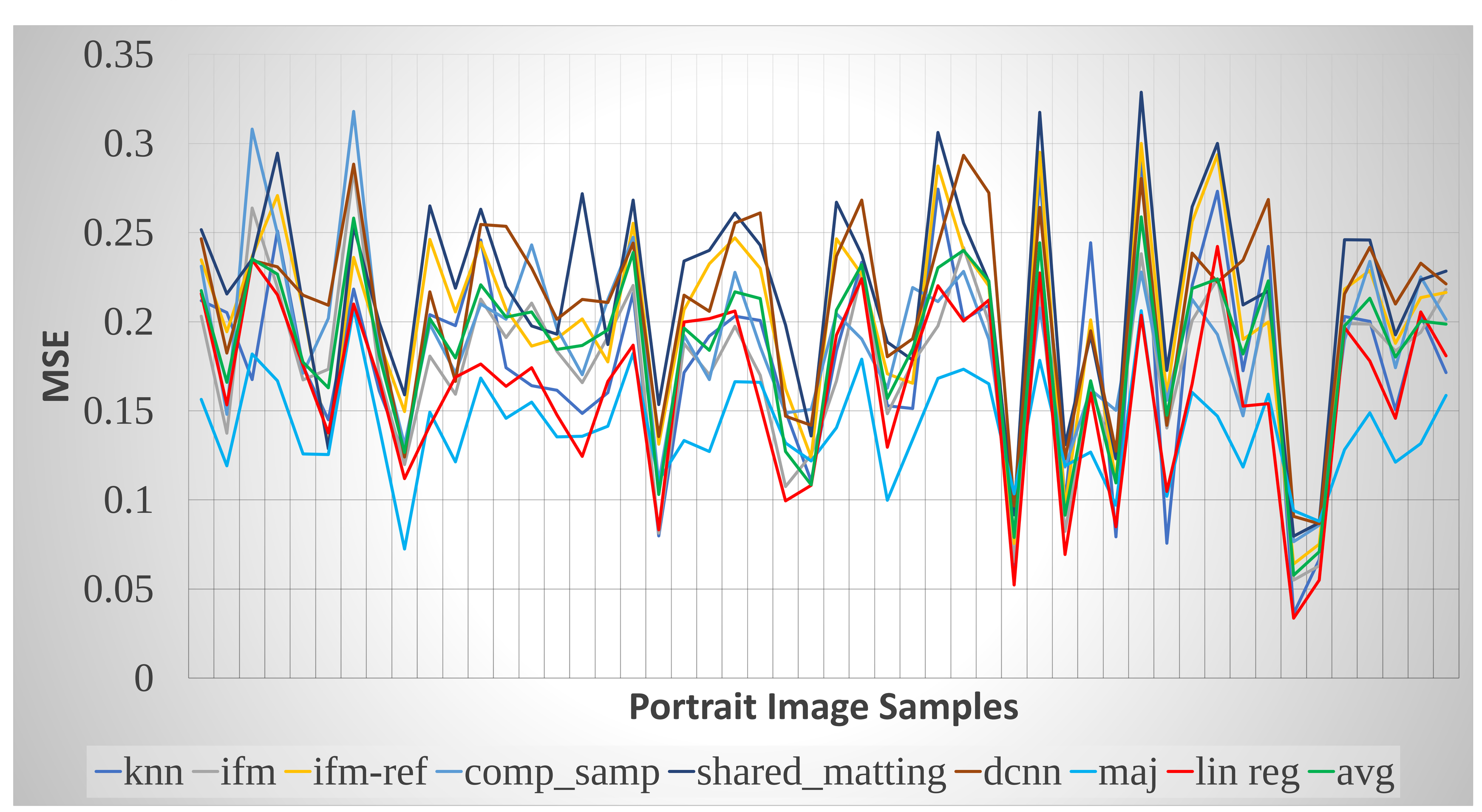


Fig. 2. Comparison of different matting approaches and ensemble learning

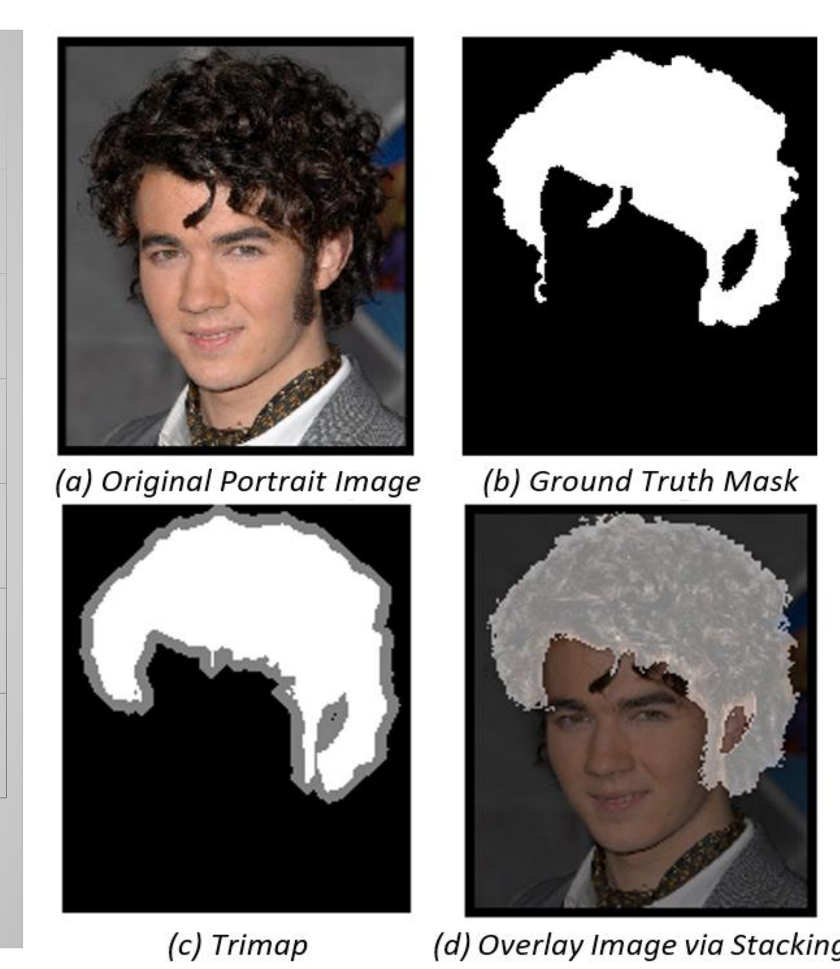


Fig. 3. Hair segmentation using ensemble of image matting

| Matting Methods | MSE on the Hair Image (Left) |
|---|---|
| KNN Matting | 0.200718 |
| Close-Form Matting | 0.256837 |
| Information-Flow Matting without Refinement | 0.219552 |
| Information-Flow Matting with Refinement | 0.217987 |
| Comprehensive Sampling Matting | 0.227906 |
| Learning-Based Matting | 0.236363 |
| Shared Matting | 0.221297 |
| DCNN | 0.214868 |
| Ensemble via Majority Voting | 0.243228 |
| Ensemble via Average | 0.193456 |
| Ensemble via Stacking | **0.17544** |

Table 1. MSEs of different matting methods