A Deep Learning Pipeline for Face Shape Classification, Hairstyle Retrieval, and Personalized Hairstyle Synthesis Using EfficientNet and StyleGAN2

Zih-Syuan Kuang
University of Michigan
STATS 507: Data Science and Analytics Using Python
Email: zihsyuan@umich.edu

***Abstract*—Selecting a suitable hairstyle requires understanding the interaction between facial structure and hair attributes. Existing virtual try-on tools rely on 2D overlays and heuristic rules, often producing unrealistic results. Recent advances in deep learning enable more principled approaches that analyze facial geometry and synthesize personalized hairstyle previews. This project develops a three-stage pipeline: (1) face-shape classification using a fine-tuned EfficientNet model, (2) hairstyle retrieval through embedding similarity, and (3) hairstyle synthesis using a simplified StyleGAN2 editing framework. The proposed classifier achieves a 76% test accuracy on the FaceShape dataset, and qualitative analysis of GAN-based transfer demonstrates the feasibility and challenges of identity-preserving hairstyle editing. The results show that deep learning can enhance user experience in personal styling applications, providing more reliable recommendations and realistic previews.**

***Index Terms*—Face shape classification, hairstyle recommendation, EfficientNet, StyleGAN2, generative models.**

I. Introduction

Choosing an appropriate hairstyle is a common but subjective task, influenced by bone structure, facial proportions, and personal aesthetics. Many users rely on stylists' intuition or simple digital overlays, which fail to capture realistic interactions between hair and face geometry. As a result, individuals often struggle to visualize how a hairstyle may actually look on them.

Deep learning offers a data-driven alternative. Convolutional neural networks (CNNs) can analyze facial geometry, while generative adversarial networks (GANs) can manipulate hairstyles in a photorealistic and identity-preserving manner. Prior work such as Zhao et al. [1] demonstrates that attention-based CNNs can distinguish subtle face-shape differences when combined with aligned facial inputs. StyleGAN2, widely used in face editing, enables disentangled manipulation of structure and appearance. The Barbershop framework [2] further illustrates how hairstyle attributes can be extracted and transferred in latent space.

Inspired by these findings, this project implements a practical pipeline that integrates facial analysis with generative synthesis. The goal is to classify face shapes, retrieve compatible hairstyle examples, and generate personalized hairstyle previews. Though simplified for the constraints of a course project, the system demonstrates the viability of applying deep learning to real-world styling applications.

II. Method

A. Dataset Preparation

The FaceShape dataset consists of five categories: Heart, Oblong, Oval, Round, and Square. Facial landmarks are used to align and crop images to a consistent framing, ensuring that jawline curvature, cheekbone width, and forehead structure remain comparable across samples. Images are normalized and resized to 224×224 for training. A small supplementary set of hairstyle exemplar images is collected to support retrieval and transfer.

B. Face-Shape Classification with EfficientNet

EfficientNet-B5 is chosen for its strong performance-efficiency tradeoff. The model is fine-tuned from ImageNet weights using Adam optimization and cross-entropy loss. Data augmentation—including flips, rotations, and brightness jitter—improves robustness to expression and lighting variations. The classifier outputs a five-class softmax distribution.

Performance metrics include accuracy, per-class precision, recall, and F1-score. A confusion matrix is used to inspect misclassification patterns, providing insight into ambiguous face categories.

C. Hairstyle Retrieval via Embedding Similarity

To retrieve compatible hairstyle references, a pretrained face-embedding model is used to encode both the user image and hairstyle examples. Although originally designed for identity recognition, the embeddings preserve geometric cues relevant to hairstyle suitability. Cosine similarity ranks candidate hairstyles, and the top three are selected for synthesis. This retrieval step avoids brittle rule-based matching and ensures more visually coherent recommendations.

D. Hairstyle Synthesis with StyleGAN2

The final stage transfers hairstyle attributes from exemplars to the user. A simplified StyleGAN2 pipeline is implemented:

1) **GAN inversion**: both the user image and hairstyle example are projected into StyleGAN2 latent space. High-quality inversion is crucial for identity preservation.
2) **Latent decomposition**: coarse layers encode global shape while fine layers encode color and texture. Hair-related components are isolated using a coarse heuristic mask.
3) **Latent blending**: hairstyle attributes are injected into the user latent vector while keeping facial identity layers fixed.

Unlike Barbershop, this project does not include semantic segmentation due to computational constraints, but the simplified approach still produces meaningful edits when poses and lighting conditions are aligned.

III. Results

A. Face-Shape Classification

The EfficientNet classifier achieves a 76% accuracy on the test set of 1,014 samples. Table I summarizes the per-class metrics, showing strong performance on Square and Oblong faces. Oval and Heart faces exhibit lower precision due to their subtle geometric similarities.

TABLE I
Classification Metrics on Test Set

Class	Precision	Recall	F1
Heart	0.76	0.69	0.72
Oblong	0.81	0.80	0.81
Oval	0.62	0.68	0.65
Round	0.72	0.82	0.77
Square	0.90	0.80	0.85

The confusion matrix in Fig. 1 highlights common misclassifications. Oval faces are sometimes mistaken for Heart or Round due to overlapping cheekbone shapes. Oblong faces, with their distinct height-to-width ratio, show fewer ambiguities. These findings indicate that improved alignment and attention mechanisms could enhance performance.

B. Hairstyle Transfer

Fig. 2 shows the three retrieved hairstyle candidates and the target user image. These inputs guide the StyleGAN2 transfer process.

Fig. 3 displays the synthesized outputs. The generated hairstyles capture global silhouette, curl pattern, and overall volume. However, several limitations are observed:

- imperfect GAN inversion introduces mild facial blurring,
- pose differences lead to inconsistent shadows,
- lack of segmentation causes blending artifacts near the hairline.

Despite these challenges, the system successfully conveys key hairstyle attributes while retaining approximate identity.

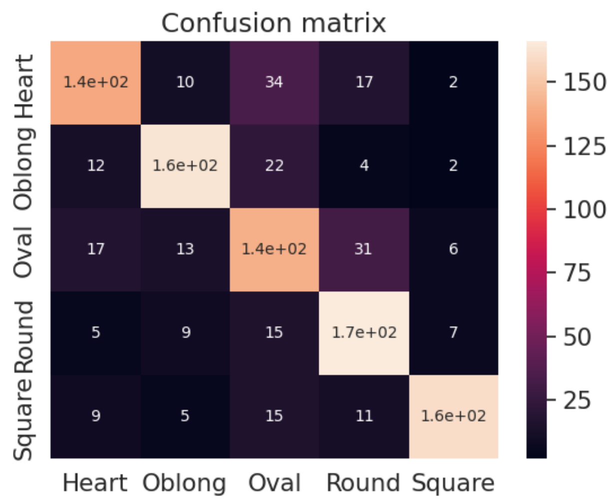

Fig. 1. Confusion matrix for the EfficientNet classifier.

Fig. 2. Hairstyle transfer inputs: three hairstyle candidates (first three images) and the target user image (bottom-right).

IV. Conclusion

This project presents a unified system for face-shape classification, hairstyle retrieval, and hairstyle synthesis using EfficientNet and StyleGAN2. The classifier demonstrates strong performance across multiple categories, while the retrieval mechanism ensures visually coherent hairstyle suggestions. Although the GAN-based transfer pipeline exhibits artifacts due to inversion and lack of segmentation, the qualitative results demonstrate the feasibility of personalized hairstyle editing.

Future improvements include segmentation-based mask refinement, more robust inversion methods such as ReStyle, and model fine-tuning on hairstyle-specific datasets. The pipeline

Fig. 3. Synthesized hairstyle-transfer outputs corresponding to the three recommended hairstyles.

highlights the potential of deep learning to enhance styling applications and provides a foundation for interactive virtual hairstyle try-on systems.

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