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CHAPTER 1

INTRODUCTION

Hairstyles are the means through which your individuality is expressed in today's society, when fashion evolves every minute and every individual seeks their unique look. StyleBlend changes the game for consumers to choose and try hairstyles. It makes personalized recommendations with virtual try-ons. StyleBlend applies techniques from StyleGAN with intelligent computer learning to display exactly how those various hairstyles would appear on you, fitting them to your face, your preferences, or current fashions trends.

The tool takes a tour of the face shape, jaw size, cheekbones, and forehead using intelligent face scanning. Following that, it comes up with hairstyle recommendations that highlight your better features. With this personalization, StyleBlend can recommend hair that suits you-from classic favorites to daring new looks. A list of carefully chosen hairstyles is there for you to view. The styles that are categorized in this group include beach waves, layers, bobs, and pixie cuts etc. These are tailored to various face forms, including long, oval, round, square, and heart.

StyleBlend's virtual try-on tool influences people by allowing its users to see how various hairstyles appear on them in real-time. As a result, users are equipped with confidence and a better understanding of their options. Apart from this, StyleBlend keeps following the trends of social media. It looks and researches popular hairstyles for consumers and keeps informing them about new ideas. StyleBlend is friendly to use and maintains its data effectively in order to ensure a safe and private experience for the users. A user's knowledge that his or her information is safe therefore helps him or her check out styles and manage his or her profiles with ease. Anyone who so desires little or more extensive changes to his or her appearance can use StyleBlend. It makes it easy to find the styles that work best.

In a nutshell, StyleBlend is a hairstyle software that is more than that, as it integrates what are considered traditional styling techniques with leading-edge artificial intelligence for new ways to play around hairstyles. This technology revolutionizes virtual styling by changing hairstyling, making it personal, interactive, and creative.

CHAPTER 2

PROBLEM STATEMENT

It can be challenging for most individuals around the globe to find haircuts that suit their unique facial structures and are stylish. Because they do not allow users to see different hairstyles on themselves and also do not offer personalized recommendations based on their face features and the latest trends, prevailing tools and apps are often deficient. This leads to people being unable to make informed hair choices and to bravely experiment with the latest styles.

To bridge this gap, there is a need for a new concept that lets the customers try out digital versions of various hairstyles on their own photos. Our approach relies on advanced facial analysis to suggest haircuts that well go with each user's facial features. For customers to access trendy and individually designed options, we also offer a trend research service meant to keep users abreast with new hairstyles. By merging customized recommendations with up-to-date trend knowledge, this application would empower users in making confident and fulfilling hairstyle decisions.

CHAPTER 3

LITERATURE SURVEY

3.1 K-Hairstyle: A Large-scale Korean hairstyle dataset for virtual hair editing and hairstyle classification

Abstract:

A large dataset of 500k high-resolution photos of Korean hairstyle is first displayed in the research work. These photographs will be assigned segmentation masks and annotated by an expert team. The scope encompasses upgrading and designing virtual justification and hairstyle category programs in the beauty sector.

Objective:

The primary task here is to introduce the K-hairstytle dataset as an important tool that can be employed for virtual hair editing and the way of hairstyle type classification. It is especially built to compensate for the shortcomings of their predecessors in terms of high-resolution, expert annotation, and segmentation masks.

Method/Approach:

1. Data Collection: Collected a significant number of high-resolution hair styles.
2. Annotation: For the dataset, professional hair stylists have tagged different features with descriptions.
3. Segmentation Masks: Created segmentation masks using the hair for the above since in addition to what had previously been given.
4. Validation: The data set performance and generalization capabilities were verified through various applications like hair style translation, beauty product recommendation and hair style classification.

Strength:

1. Large-scale Dataset: With the total number of 256,679 big size images, K-hairstyle covers two big gaps of current datasets.
2. Expert Annotation: A professional stylist-designed hair is authenticated by an expert, indicating the accuracy and quality. The evolution of this industry continues while at the same time adapting to new trends and cultural movements.

3. Validation through Applications: This app will be analyzed in terms of how it worked along with cases like translation of hair style and its classification.

Weakness:

1. Methodology Details: Due to a lack of information about sources and methods used in data collection, annotation, and validation, the aspects of reproducibility may be compromised.
2. Biases or Limitations: Paper does not in any way indicate whether biases are involved in the datasets, or the generalization which is defined by biases

Key Learnings and Future Scope:

1. Dataset Potential: K-hairstyle has potential benefit for these technologies, e.g. virtual hair dyeing and styling.
2. Machine Learning Models: All aside, as far as the practical learning is concerned, this will include understanding advanced hair editing techniques.
3. Diversity Inclusion: Increase the scope of data to include the diversity of social factors such as hair style and other attributes from different cultures.
4. Collaborating: Develop solutions that involve automatic diagnosis and recommendation systems in collaboration with computer vision specialists.

Conclusion:

Despite its inherent limitations, the K-hairstyle dataset seems to be effective for data generation in the field of virtual hair editing. As the platform continues to develop, the authors plan to make the database publicly accessible, which would support similar research and progress in the beauty tech industry.

Fig 3.1 K-Hairstyle Dataset

3.2 An Approach to Face Shape Classification for Hairstyle Recommendation

Abstract :

Paper presents a classification approach that classifies face shapes into 5 different shapes: round, oval, oblong, square, and shape.
This approach relies on a Core algorithm and a Face segmenting method, which deliver a set of images that can be used by common machine learning algorithms such as LDA (Linear Discriminant Analysis), ANN (Artificial Neural Networks), and SVM (Support Vector Machine).

Objectives :

1. Develop a comprehensive face shape classification system: The core concern here involves developing the classification system that observes five shapes of the face with such shapes being round, oval, oblong, square, and heart. Classification detail-rich allows for making personal hairstyle recommendations matching exactly clients' face shapes.
2. Utilize Active Appearance Model (AAM) and Face Segmentation Techniques: This work is oriented to two very important methods of Information and features extraction in the AAM that utilizes shape and texture information along with a segmentation technique in order to extract features from facial images.
3. Evaluating Machine Learning Methods for Feature Evaluation:However, this objective focuses on the assessment of the prominent extracted features by high-power machine-learning methods, among which are the Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN), and thirdly Support Vector Machine (SVM) methods. Since each of the algorithms of this classification of the face shapes is to be proved which will prevail over the others, that's the main reason behind this evaluation task.
4. Improve hairstyle recommendation accuracy: Not all faces are the same but faces can be put into various categories. In our system, it does exactly the same to recommend to you the hairstyle best fitting your face.

Methodology:

1. Thus, faces de facto fall into these shapes-heart, oblong, oval, round, and square-in terms of certain features like peak width ratio or hairline shape.
2. Dataset: Face of a celebrity women, after it came online and thus incorporated different

facial features.

3. Features extracted: Face measurements - dance ratios, chin width, distance chin-mouth.
4. Classification Techniques: LDA, SVM, ANN, and KNN are the most common classification models.

Transfer Learning: Last layer from the Inception v3 model, before fine-tuning is totally face shape classification and then 100% accurate.

Experimentation: Inception v3 was tested against these two datasets consisting of 500 celebrity impressions. It reached the same level of accuracy or even higher as any other classifier not based on human-crafted features demonstrating the potential of deep learning methods.

Strengths:

Inclusive Classification: Suits easily on different face shapes, few to the more common, for instance heart and diamond.

Techniques AAM and Face Segmentation: Investing AAM to build up shape and texture information and improve robustness and accuracy of the model. Consider the following sentence.

Machine Learning Flexibility: Combines with several kinds of machine learning techniques which provide more flexibility, flexibility, and adaptability for different data or applications.

Weaknesses:

Imprecise Shape Rules: It is rather difficult to find the algorithm that could eyebrow a variety of elevation, angles, and tilts with imprecise rules determining face shapes and difficulties in such forms representation mathematically, may result in misclassification.

Data Collection Method: Using Google Image Search as the main data source, it is possible that the dataset can be either unrepresentative or buried in bias.

3.3 Barbershop: GAN-based Image Compositing usingSegmentation

Abstract :

The paper proposes a new tool for GAN-based image editing, paying particular emphasis to hair editing with composite images in mind.
It addresses the problem of those tasks that do global editing like pose, expression, gender, or age and delivers a method for the picture to compose an image by selecting various features from reference images.
Yet the work is interesting with tasks like hair transfer and face-swapping due to the interdependence of visual properties that can be found at different parts of an image such as the sight of the face and the area of the hair which are strongly connected with each other.
The strongest observation learns about semantic consistency, which refers to the fact that generated images exhibit common semantic segmentation and therefore the object will move in a compositional environment with much more credibility.
The paper pursues the older approach of hair transfer based on GANs that relies heavily on in-training of inpainting networks that fail to give significant details regarding the sharp boundaries.

Objectives :

A novel composition algorithm for photo-realistic hair transference, face swapping, and other composite image editing purposes.
The innovative approach of Barbershop involves a new latent space known as FS space, which endows hyperplasticity for the spatial locality of features and accommodates a high global style degree of freedom.
FS space enables the possibility of visualizing blurred mixed images in a space horizontal to each other. Thus, it helps avoid artifact-type errors and having accurate translation as an output.
It was validated and preserved on form, texture and other key aspects, outperforming the existing state-of-the-art approaches in a user-perceived test.

Methodology:

This technique involves taking full circular composite images of the donor's with proper regions (hair and face) to create similar feature areas and finally blending them together as a new face.
Automatic segmentation reference background by name is conducted using the target semantic segmentation mask image n in orientation, guiding mask image m correctly.

It doesn't matter whether the task assigned is artifact transfer, for example of hairstyles, and then, instead of that, applying hairstyles from one pic to another in order to finish the rest of semantic segments. The stood on Yolox adds StyleGAN2 model capability to the I2S embedding algorithm, which expands SFS network spaces with specific facial manifestation to become more accurate.

Steps:

1. Remove the labeled or population images from the target segmentation. Then, prepare the segmentation mask by applying segmentation.
2. Input a reference image using LCA (Latent Codes for genes).
3. Locate interesting codes related to real audience segmentation and pictograph images. Sign in to get more help and analysis of your assigned writing tasks.
4. Construct a compound structure tensor based on the recomposed encrypted components from the aligned latent codes.
5. As, for the given task of blended images in latent space, code a mixed one to not create any artifacts.
6. Grounded on the challenge of effective setting up of alike weights for appearance codes through a masked-appearance loss function.

Strengths:

1. Flexibility in Input Formats: Retrieves multiple input formats to reconcile this with the extent of images and data types.
2. Ability to Save Output and Return Latents: This helps in tracking usage and relevant search, which can be used for students or advanced studies respectively.
3. Automatic Input Image Alignment: Originality of look because profile characteristics are correctly performed based on the given pattern.
4. Support for Diverse Resolutions: Images of different resolution rates can be resolved accurately, thereby suggesting applicability to the myriad of image sets, as well as varied usage.

Weaknesses:

1. Difficulty in Reconstructing Under-represented Features: Fine-tuning the latent space results in generalization of gems and hence produces noisy images.
2. Challenging with Occlusion: Outtakes if such hair ever covers the face of an actor, requires a special removal technique which is lately used to conceal overlapping areas, if in need.

3. Loss of Details and Structural Conservation: Registration misapprehends the subject's characteristics and, while the screen is still on the reference images, when required, it does not necessarily transfer the same masks to the target photographed area of the patient.

3.4 Style Your Hair-Latent Optimization for Pose-Invariant Hairstyle Transfer via Local-Style-Aware Hair Alignment

Abstract:

This paper aims at developing a pose-invariant hairstyle transfer method based on encoder-decoder networks, with latent optimization.
Humanizing tasks are to imagine target hairstyles while keeping fine details and solving pose differences.
The method I propose is much better compared to the existing techniques on quality and quantity criteria measurement.

Objective:

1. Make a transfer of hairstyle from images that serve as samples to objects that are on the shot surfaces regardless of the pose being the difference.
2. Therefore, preserving subtle details leads to positive results for hairstyle transfer when popular latent optimization methods are used.

Methodology:

Latent Space Manipulation:
The novel approach to that of LOHO and Barbershop makes realistic/arresting pictures depends on implicit space manipulation.
It works as the mechanism of the hidden space in StyleGAN2 to let changes to be made into latent codes for achieving their intended image modifications.
Pose Alignment and Hairstyle Transfer:Pose Alignment and Hairstyle Transfer:
The methodology of the method focuses on the process of matching the target haircut to the donor image by handling head pose variations.
In the process of latent optimization, the model naturally works out the latent codes of the target hairstyle to be in accordance with the pose and facial expression of the source image without damaging the hairstyle contour details.
Local-Style-Matching Loss:

A critical additional factor of this approach is the local style matching loss. This is an enforcement mechanism designed to preserve unique and regional-specific hair styles.
It generates the convergence region between the default target hair and the aligned one and guards against loss of local style texture for each region during the alignment.
Source Inpainting:
The strategy utilizes an occluded head source inpainting process that will replace the empty regions present in the original insource hair.
By helping to provide an appropriate label for the object to use in guiding an inpainting process, the model will then optimize codes to fill out with appropriate semantic content the occluded regions.
Blending:
Lastly, the model combines the single target head hairstyle which has been aligned with the source image and the corresponding part on the generated image to produce the final result.

A carefully balanced combination integrates the refined optimal latent codes from previous stages, creating a meaningful ecosystem with enhanced visuals.

Strengths:

1. Novel Framework: Discovers a new latent optimization approach for pose-free hairstyle transfer, which is specifically intended to cover and fix the disadvantages present in classical approaches.
2. Fine Detail Preservation: Uses locally-based hairstyle issues and distinct hairs and colors that are typical for the hairstyle during hair positioning.
3. Comprehensive Evaluation: Conducts evaluation in detail – using a variety of datasets, natural hairstyle transfer and reconstruction tasks are also included.
4. Superior Performance: Gets outstanding results, which is significantly better than the state-of-the-art methods and provided by FID scores and a high quality of visualization.
5. Robustness: The ability to tackle pose undulations well is a plus since the facial features of hair are visible across various hairstyles.

Weaknesses:

1. Computational Cost: Occurring on time demand means substantial expenses on a probabilistic optimization that is evidently due to the latent optimization limitation.
2. Occlusion Handling: Occlusions in source images pose another them to deal with, and they can distort the output as a consequence.

3. Limited Dataset Diversity: Proves its strength on FFHQ and VoxCeleb2 datasets, which gives us the reason to develop more diverse datasets in order to make its performance flexible and adaptable to different real world scenarios.
4. Hyperparameter Sensitivity: Performance can be sensitive as well to hyperparameter settings tuning, which suggests that care must be taken to find the best results by setting up a fine-tuning.
5. Incomplete Privacy Consideration: Is privacy not adequately addressed outside the face blurring [process], further avenues for discussion and provision of measures remain necessary.

Conclusion:

A novel model called our latent optimization framework that offers a better approach that harmonizes fine hair detail while aligning the target hairstyles across poses. Our development process of using FFHQ and VoxCeleb2 datasets has been through intensive experimentation. And we have used this effort to show that our approach is competitive, and that we have succeeded. Nevertheless, we still have problems resolving occlusions and optimizing hyperparameters to be solved. It would be worth pursuing extended research that features different data sources and privacy risk mitigation; the virtual clothes-trial systems and tailor-made fashion services are some of the possibilities in this regard.

3.5 StarGAN v2: Diverse Image Synthesis for Multiple Domains

Abstract:

This study provides StarGAN v2, a latest technology to make the image-to-image translation process possible across the different domains and at a high quality and diversity. It goes beyond the first version's ability by using a multitask discriminator, R1 regularization, and transfer of latent/style codes. StarGANv2 achieved SOTA among MUNIT, DRIT, and MSGAN=(StarGANv2→SOTA/between/comma MUNIT, DRIT, and MSGAN). For instance, on CelebA-HQ and AFHQ datasets, StarGANv2 surpassed the benchmarks. AFHQ dataset contingent on what is discussed herein empowers more constructive assessment of the product. StarGAN v2's versatility makes it general-purpose and is able to be generalized for many synthesis tasks, such as fine-tuning image translation and developing generative models.

Objective:

We will present StarGAN v2, the NOW cutting-edge image-to-image conversion framework, and its superiority over existing top solutions will be demonstrated through a thorough evaluation that will include major datasets.

Methodology:

However, StarGAN v2 has full functionality with multi-task discriminator, R1 regularization and latent/style codes injection contributing to produce high-quality and diverse images. To conduct the evaluation, datasets, such as CelebA-HQ and AFHQ, are used. And the latter demands more memory on the model.

Strengths:

1. Diverse Image Synthesis: GanStar v2 displays a realistic generation for many fields thus being the most superior to the predecessors.
2. Versatility: Workable with all types of formats, ranging from the fine-tuning of image transfers to the development of generative models.
3. Innovative Features: The multi-task discriminator, R1 regularization and the latent/style code injection for model training are significant for improvement in performance.

Weaknesses:

1. Complexity and Training Time: Considering additional features may result in model expansion and longer training time.
2. Limited Generalization: Besides, testing is required to measure the adaptability to new, unlike already known or dissimilar datasets.
3. Scalability Concerns: One needs to discover scaling to the large applications with use of the finite training data per domains.

Conclusion:

The starGAN v2 may be considered relatively an improvement over image producing, having better performance as well as convergence. Nevertheless, we should be striving to treat scaling, generalization, and evaluating quantitatively, whilst paying great attention to those aspects. Overall we can say that StarGAN v2 creates a platform for the researches to pursue progress in the area of multi-domain image synthesis and style transfer.

3.6 A Hybrid Approach to Building Face Shape Classifier for Hairstyle Recommender System

Abstract:

This paper suggests the origin of the hairstyle recommendations we use at present that classifies face shape using SVM-RFB. The objective of this study is the classifier improvement with a combination of hand-crafted and deep-learned features by means of concatenation and multiple-kernel learning (MKL). Three metrics are included in the results compilation: DG, DV, and DF, and the outcomes of their individual utilization and mixed application are assessed and reported as well. The paper also includes conclusions from the study and future studies that would develop feature extraction and boost recommendation accuracy.

Objective:

The aim is to implement a style of hairstyles advisory system of high quality, which can classify face shapes and recommend hairstyles corresponding to experts instructions. The core of the method is in increasing the classification accuracy by merging the topic and the spatial-geometric information into a single vector through advanced machine learning techniques like concatenation features and MKL.

Methodology:

1. Feature Extraction: Face crafted (hand-crafted) and face imagination (deep-learned) are the three elements, which describe face prominence.
2. Feature Combination: Combinations of characteristics with feature concatenation and MKL methods are utilized to derive improved feature representations.
3. Classifier Training: SVM-RBF classifier as the modeling algorithm is trained by all the combined features and the face shapes are classified with accuracy.
4. Performance Evaluation: Feature classification disciplines and a mixture of features are statistically examined by the use of the analysis techniques like confusion matrices and the accuracy comparisons.

Strengths:

1. Feature Fusion: The combined effect of hand-crafted and deep-learned characteristics bolsters accurateness, by harnessing the respective strengths of the two neural network executions.

2. Advanced Techniques: Fusing features and using MKL as a method to merge kernels is evidence of a more advanced approach to classification which boosts classification performance.
3. Comprehensive Evaluation: The study conveys a careful evaluation by using many metrics, one of them being statistical significance testing, for the purpose of validation the effectiveness of the proposed method.

Weaknesses:

1. Data Limitations: The study's performance are strongly dependent on the input training data quality and diversity which were selected for face shapes and hairstyle recognition.
2. Model Complexity: The employment of more than one type of kernel and feature concatenation may bring about higher complexity of the model, which will need fine-tuning and more resources to calculate.
3. Generalizability: The proposed method may vary in its effectiveness when it is used together with different datasets and real world applications. The method requires more assessment and adjustments to ensure effectiveness in these different scenarios.

Conclusion:

Finally the article brings out the results that the combination of hand-made and deep-learned characteristics using features concatenation and MKL techniques could drastically increase the precise classification of face shape and make it possible for automatic hairstyle recommendation systems. While the approach seems to be promising, there is still a need for additional research that will cover data limitations and complex modeling to a maximum. Also, this knowledge can be generalized for utilization in different applications across the world.

3.7 CelebHair: A New Large-Scale Dataset for Hairstyle Recommendation based on CelebA

Abstract:

To provide a sufficiently big-scaled dataset, we introduce that of CelebHair that contains 202,599 images on celebrities at random with numerous attributes including hairstyles, face shapes, and all that is facial stuff. The dataset is intended to help sophisticated machine learning solutions cope with tasks such as fashion hairstyle recommendation and simulation of a virtual hairstyle trying on. This paper covers the data collection sampling procedure that was used, the usage of Tagged

Parts/AlgoBot for hairstyle and face shape recognition and possible application such as Random Forests for recommender system and face swapping for visualization.

Objective:

The main goal of this article is to introduce the CelebHair dataset and later on start its description listing the features and also explaining what it may be used for machine learning matters relating to hairstyles and facial attributes. The paper hopes to justify the usefulness of the dataset with examples of fashion applications like hairstyle recommendations and virtual try-on, which portray how the data set can find its place in computer vision and fashion technology.

Methodology:

The methodology involves several key steps:The methodology involves several key steps:

1. Dataset Creation: CelebHair has CelebA dataset as its origin, while it is supplemented with the additional particularities of face shapes, hair styles, and face landmarks using for example, facial mark detection, CNN classifiers.
2. Classification Algorithms: CNN models are being put to use for hairstyle classification, and at the same time, YOLO v4 will be applied for facial shape classification. These models utilized for the training and evaluation purposes are deep learning architectures and are pre-trained on the subsets known to be CelebHair.

Strengths:

1. Large-Scale Dataset: The CelebHair database, consisting of numerous annotated images, serves as a great repository for the machine learning models to train with as well as to evaluate.
2. Diverse Attributes: The set is a large one that consists of wide face characteristics such as haircut, shape of the face, and more. This will accommodate complex operations for analysis and recommendation.

Weaknesses:

1. Data Quality: The paper discusses noisy images in the Hairstyle30k dataset as well as how it could trouble CelebHair that is produced using CelebA dataset.
2. Limited Evaluations: The article focused on classification thresholds but a more in depth evaluation of how the dataset performs in real situations would give more detailed information.

Conclusion:

By means of the CelebHair dataset described below, researchers and software developers from computer vision and fashion technology will be able to take advantage of a fundamental tool. It uses multi-layers of annotation and a range of attributes, which allows machine power learning (MPL) algorithms to overcome sophisticated tasks, like hairstyle recommendation or virtual try-on with good chances of success. Other experiments and upgrades are anticipated to advance the data set for the purpose of enhancing usability and provide better user experience regarding hair styles for applications.

3.8 StyleGAN Salon: Multi-View Latent Optimization for Pose-Invariant Hairstyle Transfer

Abstract:

The following paper discusses a new approach for copying hairstyles in images, aiming to give out outcomes that look genuine and real. The forthcoming project overcomes the obstacles experienced by the current solutions used both by StyleYourHair and barbershop, and aims at perfecting these masks and better utilizing multi-view latent spaces. FID scores form quality assessment and hair detail comparison with works like HairNet to highlight the importance of the proposed method.

Objective:

What the goal of this project resonates with is the refinement of the present haircut imitation methods by favoring the trait of realism and saving the identity of the input face and the hair details. Besides, the problem of adding the habitats and posing variety is considered. The objective is to try and make the model for image hair styles more correct and adaptable versus the real thing.

Methodology:

The methodology involves several key steps:

1. Better selectivity will be chosen including making up the rules of excluding undesired hair and getting a better hairstyle.
2. We want to tune the multi-view latent spaces to take the hair to look as natural as possible, and for smooth and perfect blending with the target image.
3. QoEs by FID scores and qualitative contrasts with other existing methods like StyleYourHair,barbershop, and HairNet.

4. As for the ablation studies we have to assess the behavior of separate parts of our design on the overall performance.
5. With respect to social issues, the societal negative impacts and ethical problems that are caused by synthesized images.

Strengths:

1. While the realism level and natural appearance of hair style increases compared to other methods.
2. Preserving the integrity of identity markings such as input face, even if applied in difficult cases, like an image with change in pose.
3. Additional features available include flexibility when dealing with background details, and ability to capture exact hair movements, rotation, and lighting.
4. Split testing of various methods, as well as further comparison with parallel methods, will prove outstanding results, whether it is in favor of the users or quality metrics.

Weaknesses:

1. Challenges in handling incorrect semantic regions and errors from keypoint detectors, leading to occasional failures in hairstyle transfer.
2. Potential biases and limitations in the training data or pretrained networks used, impacting performance on underrepresented groups.
3. Dependence on subjective evaluations such as user studies for preference and qualitative assessments due to limitations of existing metrics like FID scores.

Conclusion:

In conclusion, this research presents a promising advancement in hairstyle transfer techniques, showcasing improvements in realism, flexibility, and user preference compared to existing methods. While challenges such as semantic errors and biases exist, the overall results demonstrate significant strides towards generating more natural and appealing hairstyles in digital imagery. Future work may focus on refining the method's robustness across diverse datasets and addressing ethical considerations in image generation technologies.

CHAPTER 4

PROJECT REQUIREMENT SPECIFICATION

4.1 Introduction

StyleBlend is a cutting-edge platform that aims to revolutionize the hairstyling experience. It offers users a virtual try-on feature along with personalized hairstyle suggestions tailored to their unique facial features. By leveraging machine learning, latent space manipulation, and trend analysis, StyleBlend enables users to explore, experiment with, and visualize hairstyles that complement their face shape while staying updated with the latest trends from social media platforms like Instagram. With a carefully curated dataset, face shape classification algorithms, and real-time virtual try-on technology, StyleBlend seeks to enhance user confidence in selecting hairstyles that reflect their personal style and facial structure.

4.1.1 Project Scope

1. **Face Shape Analysis**:
    - **Face Shape Classification**: The system uses deep learning methods to identify distinct facial characteristics, looking at aspects like cheekbone structure, jawline shape, and forehead width. These measurements assist in identifying the user's face shape (e.g., oval, round, square) through a trained classifier.
    - **Customized Data Set**: A carefully curated dataset of 400 target hairstyles, organized by face shape, underpins the classification of face shapes. Each image in this dataset is selected with care to ensure that the hairstyle enhances the facial structure, leading to a more accurate recommendation system.
2. **Hairstyle Recommendations**:
    - **Recommendation Engine**: Using StyleGAN, the recommendation engine provides hairstyle suggestions tailored to the user's face shape and similarity analysis. It enhances these suggestions by identifying the top 5 hairstyles that closely match, ensuring users get the most relevant and attractive options.
    - **Similarity Analysis**: By exploring latent space, the similarity analysis model pinpoints hairstyles that match the user's facial features and preferences, resulting in a more tailored and visually harmonious experience.
3. **Trend Analysis**:

- **Social Media Integration**: A trend analysis module gathers data from popular social media platforms to pinpoint and integrate trending hairstyles. This feature guarantees that the recommendation database is consistently refreshed with the latest fashion trends, blending classic styles with modern ones.
- **Dynamic Style Database**: The trend analysis system has a constantly updated database of hairstyles that reflects the latest trends. This ensures that recommendations are always relevant and enhances user engagement by offering a fresh styling library.

4. **Virtual Try-On**:
   - **Real-Time Transformation**:The virtual try-on feature enables users to see how different hairstyles would look on them by overlaying these styles onto their uploaded images. Users can also adjust the alignment of the hairstyle to ensure it blends naturally with their photo.
   - **User-Controlled Customization**: Users can adjust parameters like hairstyle color and length in the try-on tool, creating a more tailored experience.

4.2 Product Perspective

StyleBlend is designed to be an easy-to-use web application that serves as your personal hairstyling assistant. It offers customized recommendations, insights into the latest trends, and lets you visualize hairstyles in real-time. The platform features a powerful image-processing backend, a user-friendly interface, and a comprehensive recommendation system to provide a seamless experience from uploading your photo to trying on a suggested hairstyle.

4.2.1 Product Features

1. **Face Shape Analysis**:
   - **Advanced Facial Classification**: StyleBlend utilizes AI algorithms to effectively analyze face shapes, placing users into specific categories based on their facial geometry. This analysis serves as the foundation for personalized hairstyle suggestions.
   - **Curated Data Accuracy**:The platform’s unique dataset, organized by face shape, improves recommendation precision by proposing hairstyles that genuinely enhance the user's facial structure.
2. **Hairstyle Recommendation Engine**:
   - **Top 5 Similar Hairstyles**: The recommendation engine uses similarity analysis to create a ranked list of the five most appropriate hairstyles, increasing user confidence in the suggested choices.

- ○ **Continuous Learning**:As the system gathers more user data, the hairstyle recommendation model adapts, learning from user interactions and feedback to offer increasingly relevant suggestions.

3. **Virtual Try-On**:
    - ○ **Seamless Image Processing**: The virtual try-on feature ensures accurate hairstyle alignment and blending, making certain that the hairstyle looks naturally integrated with the user's face.
    - ○ **Realistic Visualization**: By simulating lighting and texture adjustments, StyleBlend's try-on tool produces highly realistic images that demonstrate how the hairstyle would appear in real life.
4. **Trend Insights**:
    - ○ **Social Media Data Mining**: This feature keeps StyleBlend's hairstyle database up-to-date by collecting trend information from Instagram and other social media platforms, ensuring the latest styles are included in the service.
    - ○ **User-Relevant Recommendations**: By customizing suggestions to align with current trends, the trend insights feature helps users stay ahead in hairstyle fashion.

4.2.2 Operating Environment

The main way that StyleBlend functions is as an online platform that can be accessed on desktop computers using ordinary web browsers. In order to enable the secure and effective movement of data between the Windows and MacOS operating systems, it operates as an Internet of Things (IoT) device and needs internet connectivity.

4.2.3 General Constraints, Issues, and Dependencies

Constraints:

Limitations: People frequently utilize social media as a forum to carefully cultivate their appearance, and the quantity and caliber of user-uploaded photos may result in inaccurate face feature analysis and haircut suggestions. Another important consideration is the credibility of trend providers.

Assumptions:

The masses would be having access to digital devices with capacity for capturing photographs or images that users can upload for analysis. This user's willingness to submit some of their pictures or data for evaluation, along with providing example recommendations or particular hacks, will make the collected data relevant. These would serve as examples of trustworthy sources for trend analysis and sound modeling.

Dependencies:
A neural network developed by StyleBlend learns from ml-supervised processes, which get enhanced by facial analysis, hairstyle suggestions for women, and, moreover, retrieval of fashion trends in females through the software algorithms of the application. This open API data integration adds value to the system by linking it with a trend analytics library, thus expanding its functionalities. Such a base may need to improve data sources.

4.2.4 Risks

1. Data Privacy: Exploitation of imagery and information shared by users has much probability to be misapplied hence developers of the system will have to press hard to put security measures and data policies to guard against effects of privacy.
2. Algorithmic Bias: Performance errors may come along as a result of bias of algorithms in analysis of facial features and recommendations of hairstyling and even require more control and investigations to be free from any bias, hence fairness.
3. Technical Challenges: Technical risk of any systems failure is almost inclusive of downtime in the system, performance bottleneck, or events of incompatibilities across different devices and browsers required full proactivity to maintain and running 24 hours a day.
4. User Acceptance: Risk of low floor in user adoption or usage of the platform due to issues of usability concern, unawareness, or dissatisfaction with recommendations made by the system calls for a user feedback mechanism and revamping the platform for a better experience..

4.3 Functional Requirements for StyleBlend

1. **Image Upload and Preprocessing**
    - **Input:** Users upload images from local storage
    - **Functionality:**
        - The posted image will be processed by the system with the right amount of cropping, resizing, and first alignment to extract as many facial features as possible. Some image enhancement techniques, including noise reduction and contrast improvement, will be applied for easy and accurate analysis of the face and consequent styling results.

   - **Output:**An image that is standardized and preprocessed for facial feature analysis and hairstyle recommendations.
2. **Face Shape Classification**
   - **Input:** Processed images of the user's face.
   - **Functionality:**
     - The system works by employing machine learning models in the analyzing of key landmarks on the user's face like the jawline, cheekbones, and forehead into other classifications of shapes such as oval, round, square, or heart-shaped.
     - This is important for proper hairstyle recommendation that matches the specific shape of the face.
   - **Output:** It will output on the face shape identified, which will then be used for filtering hairstyle recommendations appropriate to that shape.
3. **Hairstyle Recommendation Engine**
   - **Input:** Classified face shape
   - **Functionality:**
     - **Similarity Analysis:** The system will refer to its proprietary database of 400 hairstyles classified by their compatibility to specific face shapes. That will allow the system to determine hairstyles consistent with user's facial attributes by applying facial feature extraction techniques and machine learning models.
     - **Top-5 Similar Hairstyles:** For every user, the system will undertake similarity analysis for finding the top five hairstyles based on facial attributes. The algorithm compares the face shape and other features of the user with that of the target hairstyle and ranks them on the basis of similarity and relevance.
     - Such engines quite completely either consider stylistic preference variations or the influence of trends and period constructs content in a very diverse way and includes everything from modern styles through trendy looks all the way to timeless cuts.
   - **Output:** Five recommended hairstyles, according to similarity analysis and compatibility with the user's face shape, should also allow the user to view more styles.
4. **Virtual Try-On Feature**
   - **Input:**A selected hairstyle from the recommendations.

- **Functionality:**
  - Based on image processing and blending techniques, the system will take the user-uploaded photo and blend with the selected hairstyle. The size, angle, and alignment of the hairstyle will be adjusted depending on the user's facial features, providing a realistic simulation on how the hairstyle looks to him/her.
- **Output:**A realistic representation of that hairstyle on the user's face so that the user can see whether the fit is right or not.

5. **Trending Hairstyles Analysis**
   - **Input:** Data generated through social media platforms, like Instagram, and online style references.
   - **Functionality:**
     - It collects and analyzes trending hairstyles data, current fashion trends with popular styles, with the dynamic trend analysis, which allows showing always the latest looks relative to one's own style.
   - **Output:** A shortlist of trending hairstyles
6. **User Interface and Experience Optimization**
   - **Input:** User interaction and feedback.
   - **Functionality:**
     - The platform guarantees an intuitive, user-oriented interface that allows effortless navigation between hairstyle recommendations, virtual try-on, and trend insights. Responsive design supports continuous interaction across various devices- desktops, tablets, and smartphones.
   - **Output:** This will ultimately result in streamlining and optimizing an end-user experience, which promotes engagement and ease.

4.4 External Interface Requirements

4.4.1 User Interfaces:

1. Web Interface: For online access on desktops, with the common browsers, this must also be accessible using mobile optimised platforms.
2. Upload an Image: The simple interface must be provided to the users where they will upload from image files, social, or from the device.
3. Virtual Try-on: let user choose the hairstyle to be virtually tried on with an appropriate matching of the facial profile

4. Image Generation: Final output with hairstyle curated on the face of the user.

4.4.2 Hardware Requirements:

1. Client Devices: Heterogeneous devices supporting several platform types like desktop systems, laptops, and standalone electronic devices like tablets and smartphones.
2. Internet Connection: An online platform can only access through a stable internet to be able to upload images.
3. Camera: Provides users to take self-shot photos for the purpose of facial recognition and immediate performance evaluations (virtual try on).

4.4.3 Software Requirements:

1. Web Server: Implementation of the application and firewalls to host the platform while providing secured access to users would be obligatory.
2. Image Processing Library: Make use of your libraries and frameworks for all of these functions, from picture processing and identifying facial features to making virtual hairstyles. Write the programs necessary to make the software that allows you to analyze pictures, detect facial features and virtual hairstyles as well.
3. Machine Learning Frameworks: Build on various machine learning libraries like TensorFlow or PyTorch for facial recognition, trend analysis, and hair style recommendation.
4. Database Management System: A reliable database management system (e.g. MySQL, MongoDB) should be acquired for the storage of user data, images, and hair types.

4.5 Non-Functional Requirements

4.5.1 Performance Requirements:

1. Response Time: Make sure that quick interaction performances of virtual reality tools, analytics, virtual try on, etc. are unaffected for a seamless system for the user.
2. Scalability: The framework should be implemented and contain holistic resource management with adding users achievable without degrading performance.
3. Reliability: Removal of overtime through the installation of substitute servers, provider load balance, and fault tolerant architectures will take care of connection interruption.

4.5.2 Safety Requirements:

1. Privacy of information: Collection of data should not violate the privacy rights of the user and his sensitive information. For this purpose, compliance with data protection regulations is to be followed and the collected data be encrypted or restricted access.
2. User Authentication: Ensuring the safety of user identification through the use of secure authentication tools such as two-factor authentication confirms the identity of a user and reduces the chances of unauthorized access to profiles and data.
3. Image Security: Users uploaded pictures should be sanitized from unauthorized copying or misuse using authorization controls along with encryptions.

4.5.3 Security Requirements:

Platform Security: Amplifying the system defense against root threatening factors, which brace it against source threats degrees like XSS, SQL Injection and session hijacking.

Regular Audits: Establishing a system for regular security audits and performance checks would work excellently in seeking out possible vulnerabilities that could compromise the system in future.

Secure Communication: HTTPS-secure crypto within the client-server by eliminating active tapping, packet analyzers, or interception of data on the transmission wiring of information along the network..

CHAPTER 5

SYSTEM DESIGN

5.1 Goal:

StyleBlend proposes to develop a platform to cater style with scalability, efficiency, and usability while providing personalized hairstyle recommendations and virtual try-ons for users. With the application of advanced techniques in machine learning, StyleBlend will analyze facial features and user preferences to provide customized hairstyle recommendations. Further, it incorporates a virtual try-on module to show how various hairstyles would look on new hairstyles before opting for them. The platform can eventually be seen as a connector between fashion and technology; a user-friendly venture for the user to explore new looks confidently.

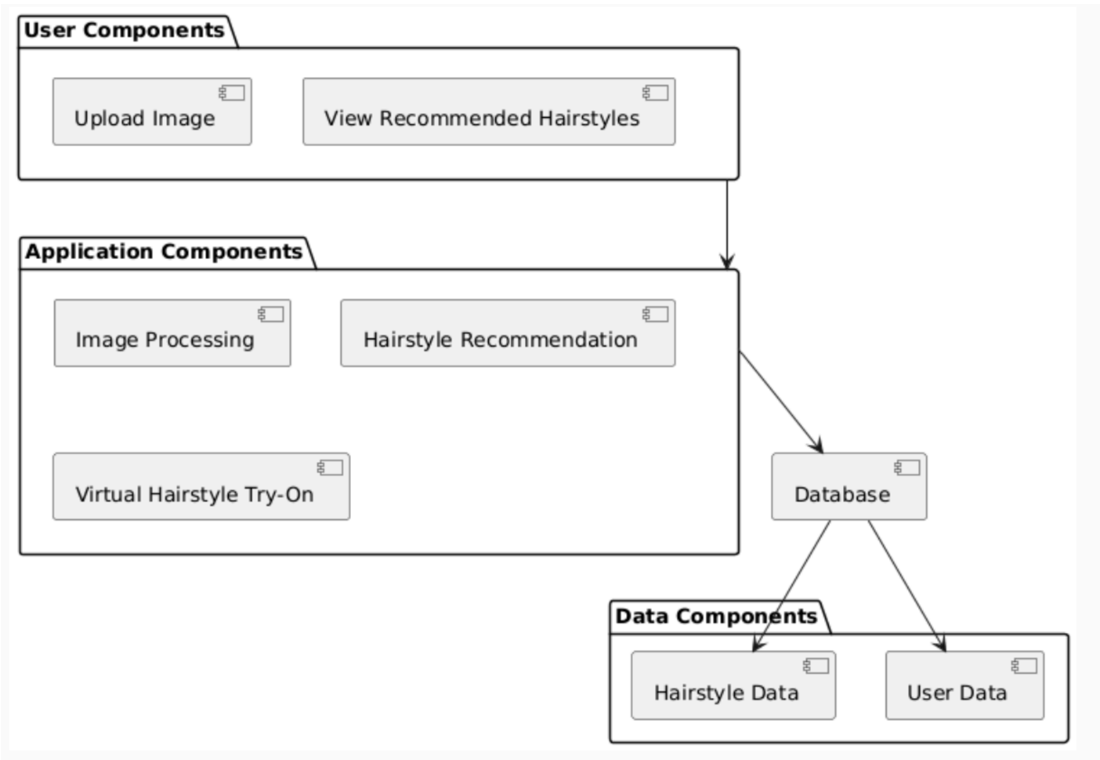


Fig 5.1 Design of the proposed system

5.2 Components of the System:

5.2.1 Hardware Components:

1. **Computers**:
    - Desktops, laptops, and mobiles are the main platforms that the users will be using to interact with the system. Therefore, the platform must be able to support multiple types of devices for seamless use across all platforms.
2. **Cameras**:
    - Users may upload images taken with their device cameras or attached webcams. These cameras are critical because they capture high-quality facial images necessary for accurate face shape classification and conducting virtual try-on simulations.
3. **GPUs**:
    - These powerful GPUs are intended to implement real-time image processing, feature extraction, and virtual try-on simulation with machine learning models. The GPUs perform fast and efficient calculations over large datasets to accomplish the tasks quickly in deep learning works, such as generating hairstyle transformation.

5.2.2 Software Components:

1. **Backend Framework**:
    - **Python/Django** or **Node.js**: will be applied, the backend logic - user requests, data storage, and machine learning models through API calls-will be handled.
    - **RESTful APIs**: This can be relied on smooth switching between front and back ends for data exchange by image upload, analysis, and visualization.
2. **Machine Learning Models**:
    - **TensorFlow** or **PyTorch**: These will be the main frameworks to implement models for facial features extraction, face shapes classification, and hairstyle mailing recommendation. It analyses images of the user for defining facial landmarks, face shape classifying and hairstyle recommendations.
    - **Face Shape Classification Model**: This model finds out the face shape of the user from the identified face landmarks and features (for example: round, oval, square).
    - **Similarity Analysis Model**:With this model, the facial features of a user will be compared to a set of 400 target hairstyles collected into a custom dataset in order to

find the five most similar hairstyles through metrics like Euclidean distance and cosine similarity.

3. **Database**:
   - **MongoDB/MySQL**: A reliable database will hold all profiles of users along with hairstyle images, user interaction data, and system logs. Store images with MongoDB while managing structured data as user profiles and preferences in MySQL.
4. **Cloud Services**:
   - **AWS/Google Cloud**: This is where machine learning models will host and process much data. Services avail scalability in cloud for the deployment of models for efficient handling of increasing user base with images.
   - **AWS S3**: Store user images and hairstyles to enable quick access.
5. **Image Processing Libraries**:
   - OpenCV and Dlib, FaceRecognition, etc., will be used in the process of developing facial feature detection, image preprocessing, and virtual try-ons.

5.3 Workflow Overview:

1. **User Interaction**:
   - Users may upload an image or take a picture of themselves with their camera.
   - The facial recognition model analyzes the features of the user's face and recognizes the shape of his / her face.
2. **Face Shape Discovery**:
   - The uploaded image is subjected to the identification of landmarks on the face and determining the shape of the face (e.g., round, square, heart shape).
3. **Hairstyle Recommendations**:
   - A similarity analysis model matches facial characteristics of the user with 400 target hairstyles available in a custom dataset. It identifies the 5 hairstyles that most closely fit the user's face shape and preferences.
   - These suggestions are further refined trending for users to get the latest and freshest hairstyle ideas.
4. **Virtual Try-On Simulation**:
   - Once the user has chosen a specific hairstyle, the system tries it virtually, i.e., the chosen hairstyle gets placed on the user's image. Hair position, angle, and size are modified to match the user's face shape against the corresponding dimensions.

5. **Real-Time Personalization**:
   - The system further imbibes learning through user feedback into subsequent recommendations for hairstyles and try-on simulations, such that it leaves a personalized touch to every interaction by users.

5.4 Hardware and Software Requirements:

Hardware Requirements:

1. **Devices**:
   - Desktops and laptops, tablets, and even smartphones for running web-based applications. Devices should come with a camera for image capturing and house a webcam for pre-processing images.
2. **GPUs**:
   - High-performance graphics processing units (Consoles include Nvidia Tesla (T4), Quadro, or any other CUDA-compliant ones) to make the training and inference of deep machine learning models highly efficient, especially in the case of virtual try-on simulations and real-time face shape analysis.

Software Requirements:

1. **Backend Frameworks**:
   - FastAPI or Flask will be used to serve machine learning models with REST APIs.
   - Ngrok is a globally distributed reverse proxy that protects and accelerates applications and network services.
2. **Machine Learning Frameworks**:
   - TensorFlow or PyTorch for building and training models that are focused on extracting facial features, classifying face shapes, and recommending hairstyles.
   - Scikit-learn for using classical machine learning models and for additional data processing tasks.
   - Keras deep learning model for determining similarity from facial profiles
3. **Database Management**:
   - A database that uses data such as images and hairstyle metadata is MongoDB.
   - MySQL-Structured Data Storage is about user profiles and interaction data.
4. **Image Processing and Computer Vision Libraries**:
   - OpenCV, Dlib, FaceRecognition: Detects, aligns, rotates, translates, and preprocess facial features.

5. **Cloud Services**:
    - AWS or Google Cloud: Both can be used to provide hosting services and system scalability.
    - AWS S3- A cloud storage service that enables efficient image storage and retrieval.
    - Google Cloud AI/ML Services: Provides model hosting and distributed processing services.
6. **Other Tools**:
    - CUDA is used to enable parallel processing and accelerate the image-generating tasks.

5.5 Development Tools and Technologies:

- **Frontend Development**: By using HTML, CSS, JavaScript create front diverse interface for the user while uploading try-on images, exploring recommendations.
- **Backend Development**:
    - To add real-time image analysis and serve machine learning models, FastAPI or Flask should be employed.
    - Ngrok is also known as a globally distributed reverse proxy that manages secure and speed applications and their related network services.
- **Machine Learning**:
    - Install deep learning models with TensorFlow, Keras, or PyTorch to accomplish tasks such as facial feature extraction, classification of face shapes, and recommending hairstyles.
    - Scikit-learn can also be used for other tasks, like clustering hairstyles or analyzing user preferences.
- **Cloud Platforms**:
    - AWS s3 or Google Cloud could find use in hosting and scalability as well as distributing load processing.
- **Image Processing Libraries**:
    - It holds OpenCV, Dlib and Face Recognition for image pre-processing, landmarking the facial structures, and performing virtual try-ons.
- **Database**:
    - MongoDB as an unstructured repository for images.
    - MySQL should benefit from structured data such as user profiles and interaction logs.

CHAPTER 6

PROPOSED METHODOLOGY

6.1 Proposed Methodology:

TThe following core steps are to be included in the methodology the StyleBlend project will propose.

1. Virtual Hairstyle Transformation

Overview: Briefly, this feature allows the user to try out hairstyles while taking input and processing through an advanced algorithm. Users upload their images and transform them into another look.

Steps:

- **Image Upload**
  The user uploads a high-resolution image which explicitly features all aspects of the face.
- **Image Preprocessing**
  The uploaded image is preprocessed to resize it appropriately such that it fits into the input size that would be used by our model. This step of resizing has been optimized for the feature detection accuracy and compatibility with the next transition stage.
- **Face Alignment**
  We use Dlib's 68-point facial landmark detection to locate exactly and align in the face the features. It is meaningful for the seamless hairstyle transfer because the face has to be rightly oriented for the hairstyle transfer operation.

$$L = \mathrm{Dlib}(F)$$

- **Target Hairstyle Selection**
  Users will have the option of selecting a desired hairstyle from a large number of curated options that have been organized into folders based on different face shapes. This taxonomy will guarantee that the selected hairstyle will be the best suitable for the particular user's facial features, all of the images serving as a target for transformation in users' exploration of various looks and styles.

- **Hairstyle Transformation using StyleGAN**
  The Style-YOUR-HAIR model is the one that performs the generation of the hairstyle transformation whose effect is realized by performing the manipulation of latent space of the model blending in the selected hairstyle with the given facial features so that the outcome looks completely natural and realistic.
- **Image Blending and Final Output**
  Eventually, multi-resolution blending techniques merge the transformed hairstyle onto the user's image and help to maintain vital features such as texture as well as lighting that produces a smooth and coherent final output which looks very natural and personalized.

2. Tailor-Made Hairstyles Suggestions

Overview: The feature will give personalized hairstyle suggestions according to the facial shape of the user, adding much more to the overall user experience.

Steps:

- **Face Shape Detection:** System employs a pre-trained model to classify the user's face shape (e.g., oval, square, heart, long, round) when uploading an image. The classification is crucial to filter out the hairstyles recommendations.

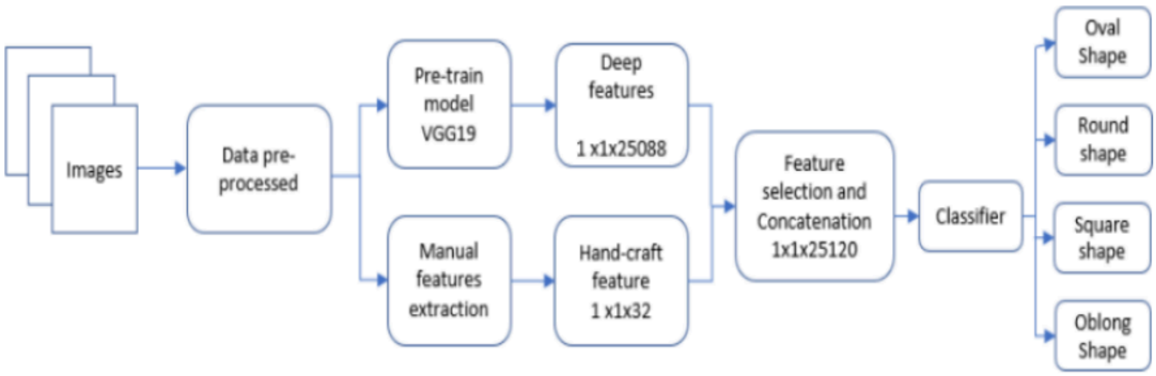


Fig 6.1 Face Shape Detection model

- **Dataset Preparation:**
  - Filter the FFHQ image collection for pictures of women with clear hairstyles.
  - Detect these women's face shapes and subdivide them in 5 folders depending on the detected face shapes.

- **Similarity Analysis:** Here, the user might run a similarity analysis on his/her face with those in the filtered dataset. Metrics measuring such an analysis can either be a cosine similarity or Euclidean distance in the feature space gotten from a facial recognition model.
- **Recommendation Generation:** From the particular folder (identified by the detected face shape), extract the relevant top five hairs closely compared to the user's facial features for user selection.

3. Trending Hairstyle Extraction

Overview: This is a minor feature but worth mentioning. Because it will give the most popular hairstyle trends-borrowed from popular media.

Steps:

- **Data Scraping:** Data Scraping: Web scraping for the purposes of accumulating data from Instagram with the research of hashtags concerning hairstyles (e.g., #hairstyles, #hairtrends).
- **Data Processing:**
    - Collect relevant images and metadata, such as likes and comments, in order to measure popularity.
    - Filter and save those trending hairstyles for display to the user.
- **User Display:** A list of the trending hairstyles, which can be viewed by the users and not used for virtual try-on.

6.2 Proposed Architecture:

This StyleBlend architecture will house the components and technologies such as: The StyleBlend architecture will accommodate the following components and technologies; with it:

1. User Interface: This essentially means the operating panel where StyleBlend clients can indulge in some hairstyle play, search some cool trends, and get tailor-made suggestions.
2. Backend Services (Python/Django or Node.js): the system will come with an inbuilt set of APIs for the HTTP endpoints through which data processing retrieves, serves the machine-learning model, and connects to the database for smooth operations.
3. Machine Learning Models and Libraries: A combination of decision tree, random forest, and support vector machine models will take the input (s) from the user and analyze their face features to come up with a hairstyle recommendation. Some of these libraries include pytorch , numpy, alignment, embeddings, skiimage, etc.

4. Database (MySQL or MongoDB): This type of database maintains the user's chronology, hairstyle choices, and trends of information to really support the recommendation algorithms and boost user interaction.
5. Cloud Services (AWS, Google Cloud): We choose the StyleBlend platform because of the scalability, reliability, and ability to conjoin with other cloud based services (like other technologies).

This design above shall ensure that users will have no hassle accessing the platform, using the site without any challenge, and be able to select a hairstyle of his/her choice or favorite with ease.

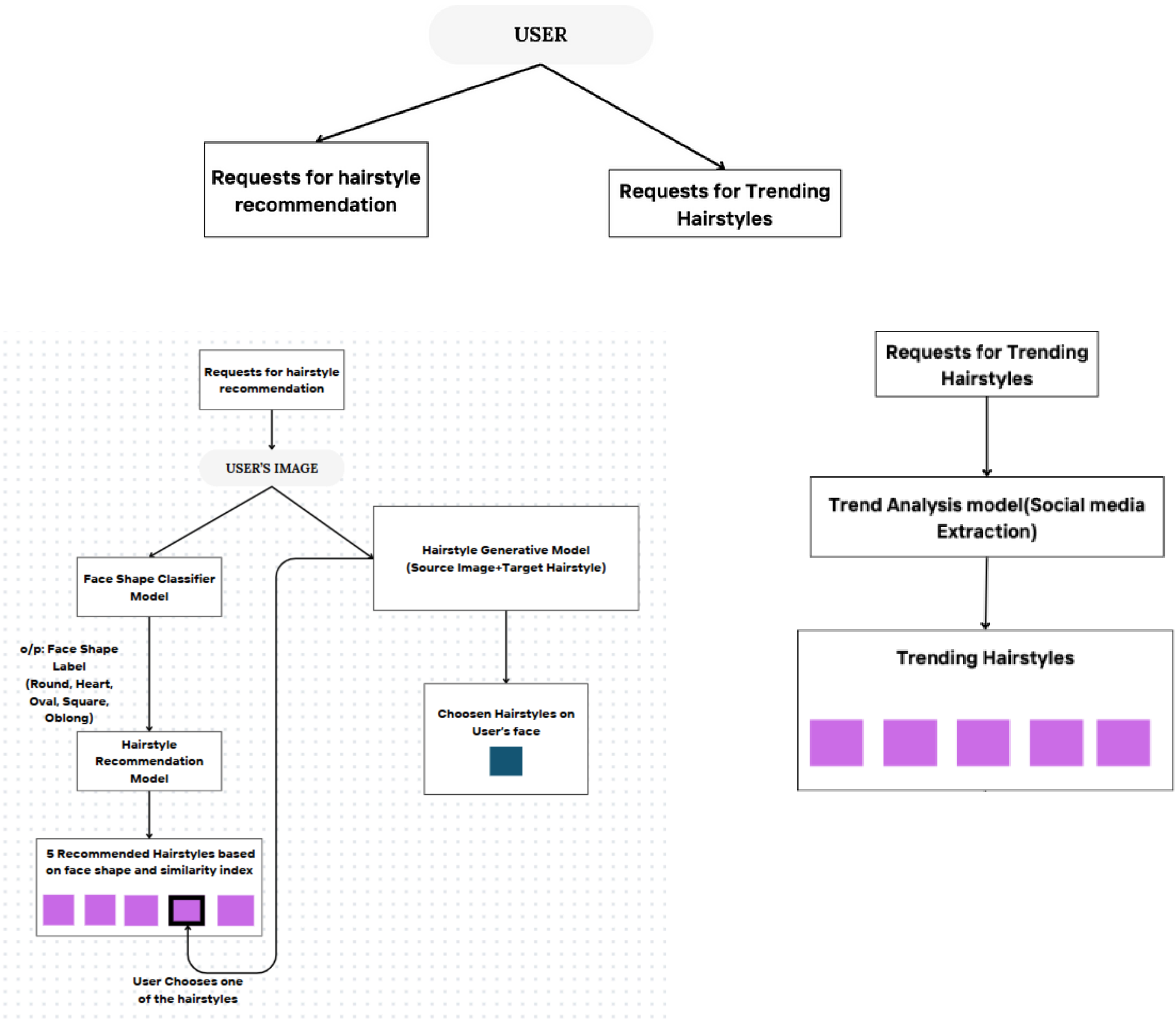


Fig 6.2 Project Workflow

CHAPTER 7

IMPLEMENTATION AND PSEUDOCODE

```python
import os
import shutil
import numpy as np
from deepface import DeepFace
from scipy.spatial.distance import cosine, euclidean, cityblock
from IPython.display import display, Image
import torch
import torchvision.transforms as T
from torchvision import models
from PIL import Image as PILImage
from torch import nn

# Paths
MODEL_PATH = "/content/drive/MyDrive/Style-Your-Hair/best_model (1).pth"
user_image_path = '/content/drive/My Drive/Style-Your-Hair/Celebrity_imgs/source.png'
base_folder_path = '/content/drive/My Drive/Style-Your-Hair/Celebrity_imgs'
save_path = '/content/drive/My Drive/Style-Your-Hair/ffhq_image/target.png'

# Class mappings for face shapes
class_to_idx = {
    "Oval": 0,
    "Round": 1,
    "Square": 2,
    "Heart": 3,
    "Long": 4
}
idx_to_class = {v: k for k, v in class_to_idx.items()}

# Load and setup the face shape classifier
device = "cuda" if torch.cuda.is_available() else "cpu"
model = models.efficientnet_b4(weights=None)
num_classes = len(class_to_idx)
model.classifier = nn.Sequential(
    nn.Dropout(p=0.3, inplace=True),
    nn.Linear(model.classifier[1].in_features, num_classes)
)
model.load_state_dict(torch.load(MODEL_PATH, map_location=device))
model = model.to(device)
model.eval()
```

```python
# Transformation for input images
inference_transform = T.Compose([
    T.Resize((224, 224)),
    T.ToTensor(),
    T.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])

def classify_face_shape(image_path):
    """
    Classifies the face shape of the given image.
    """
    try:
        img = PILImage.open(image_path).convert("RGB")
        input_tensor = inference_transform(img).unsqueeze(0).to(device)
        with torch.no_grad():
            output = model(input_tensor)
            _, predicted_idx = torch.max(output, 1)
            return idx_to_class[predicted_idx.item()]
    except Exception as e:
        print(f"Error classifying image {image_path}: {e}")
        return None

def get_face_embedding(image_path):
    """
    Extracts face embedding from the given image path using DeepFace.
    """
    try:
        analysis = DeepFace.represent(image_path, model_name='VGG-Face', enforce_detection=False)
        return analysis[0]['embedding']
    except Exception as e:
        print(f"Error processing image {image_path}: {e}")
        return None

def calculate_composite_similarity(embedding1, embedding2, weights=(0.4, 0.4, 0.2)):
    """
    Calculates composite similarity score between two face embeddings.
    """
    if embedding1 is None or embedding2 is None:
        return 0
```

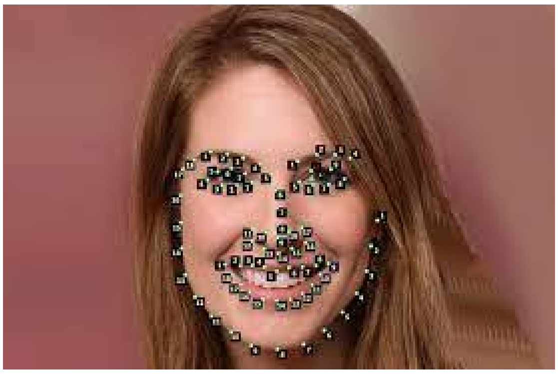


Fig 7.1 Facial Landmark Detection

```python
def calculate_composite_similarity(embedding1, embedding2, weights=(0.4, 0.4, 0.2)):
    """
    Calculates composite similarity score between two face embeddings.
    """
    if embedding1 is None or embedding2 is None:
        return 0

    cos_sim = 1 - cosine(embedding1, embedding2)
    euclid_dist = euclidean(embedding1, embedding2)
    manhattan_dist = cityblock(embedding1, embedding2)

    # Normalize distances and calculate weighted composite score
    norm_euclid = 1 / (1 + euclid_dist)
    norm_manhattan = 1 / (1 + manhattan_dist)
    composite_score = (weights[0] * cos_sim) + (weights[1] * norm_euclid) + (weights[2] * norm_manhattan)
    return composite_score

def find_most_similar_in_shape(user_image_path, shape_folder_path):
    """
    Finds the top 5 most similar celebrities to the user image within the specified shape folder.
    """
    user_embedding = get_face_embedding(user_image_path)
    if user_embedding is None:
        raise ValueError(f"Could not get embedding for user image: {user_image_path}")

    similarities = []
    for celeb_image in os.listdir(shape_folder_path):
        celeb_image_path = os.path.join(shape_folder_path, celeb_image)

        try:
            celeb_embedding = get_face_embedding(celeb_image_path)
            similarity = calculate_composite_similarity(user_embedding, celeb_embedding)
            similarities.append((celeb_image_path, similarity))
        except Exception as e:
            print(f"Error processing {celeb_image_path}: {e}")

    # Sort by similarity and return top 5 results
    return sorted(similarities, key=lambda item: item[1], reverse=True)[:5]
```

```python
def display_top_images(top_5_similar):
    """
    Display the top 5 images with similarity scores and allows manual selection.
    """
    for idx, (celeb_path, score) in enumerate(top_5_similar):
        display(Image(celeb_path, width=200, height=200))
        print(f"{idx+1}. Celebrity: {os.path.basename(celeb_path)}, Similarity: {score:.4f}")

    while True:
        try:
            index = int(input("Select the image number (1-5) you want to save: "))
            if 1 <= index <= len(top_5_similar):
                selected_image = top_5_similar[index-1][0]
                print(f"Selected Image: {selected_image}")
                return selected_image
            else:
                print("Invalid selection. Please choose a number between 1 and 5.")
        except ValueError:
            print("Invalid input. Please enter a number between 1 and 5.")

# Step 1: Classify the face shape of the user image
predicted_shape = classify_face_shape(user_image_path)
if predicted_shape:
    print(f"Predicted face shape: {predicted_shape}")

    # Step 2: Find top 5 similar images within the predicted face shape folder
    shape_folder_path = os.path.join(base_folder_path, predicted_shape)
    top_5_similar = find_most_similar_in_shape(user_image_path, shape_folder_path)

    # Display top 5 images and similarity scores, and let the user select one
    selected_image = display_top_images(top_5_similar)

    # Save the selected image to the specified path
    if selected_image:
        shutil.copy(selected_image, save_path)
        print(f"Selected image saved to: {save_path}")
else:
    print("Failed to classify face shape.")
```

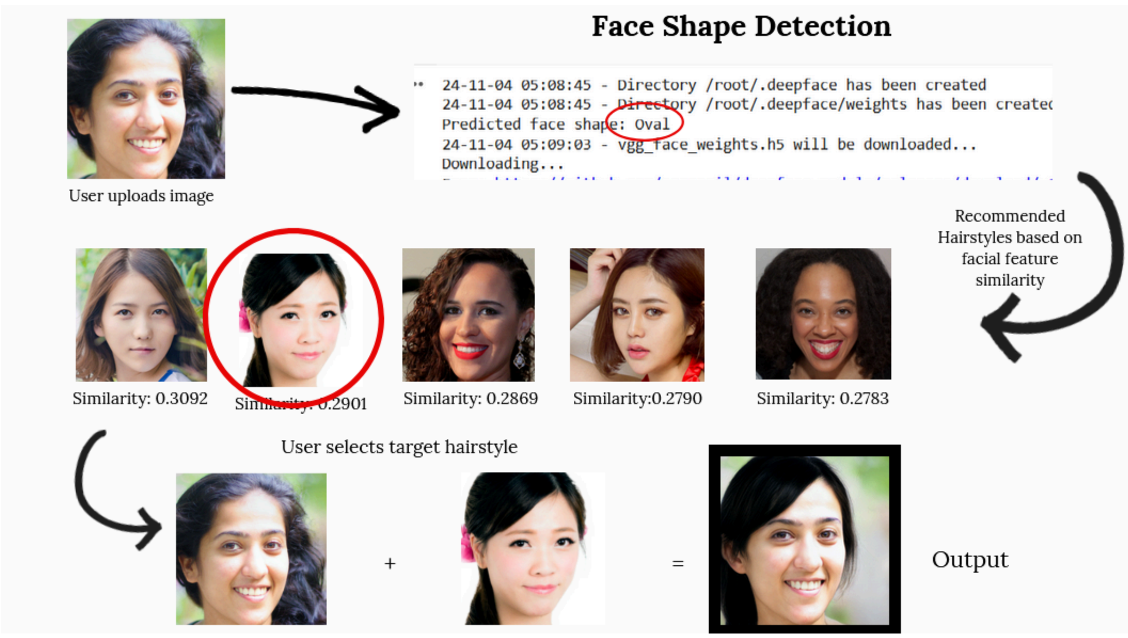
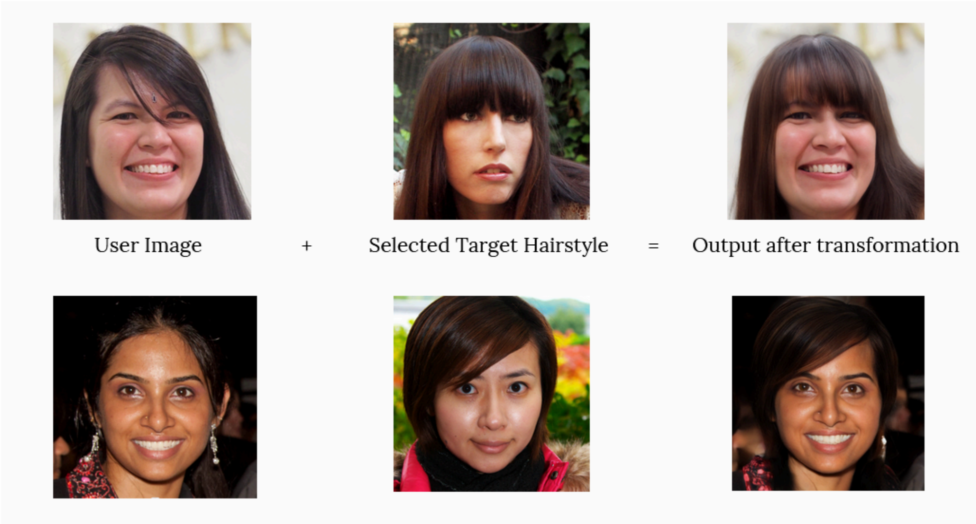


Fig 7.2 Face Shape Detection, Similarity Analysis and Hairstyle Recommendation



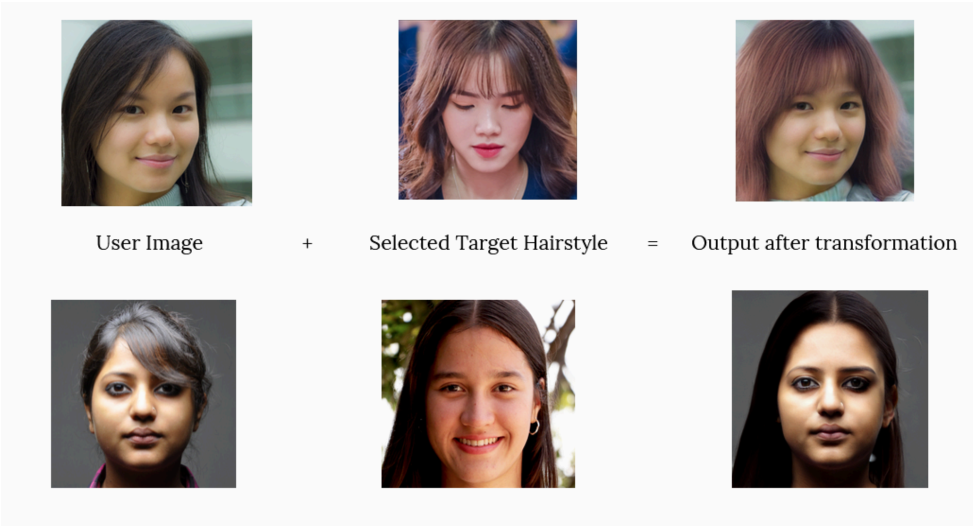


Fig 7.3 Outputs of Virtual Transformations

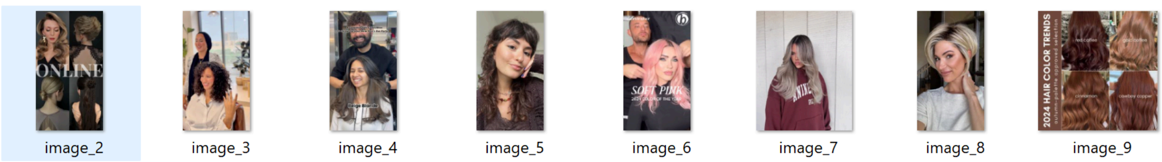


Fig 7.4 Trend Extraction

CHAPTER 8

RESULT AND DISCUSSION

Having completed the second phase of our capstone project, we have well positioned ourselves towards the finish line. We built a fully-fledged web application with features such as virtual try-on, where users can see products on virtual models, a recommendation system that provides personalized hairstyles based on user preferences and trends, and advanced trend analysis capabilities, which can help them gain insights from social media data. Achievements during this phase include perfecting the extraction of trending images from social media platforms, accurately identifying facial landmarks using Dlib, and delving into research and technologies like OpenCV to gain a good understanding of the techniques and applications.

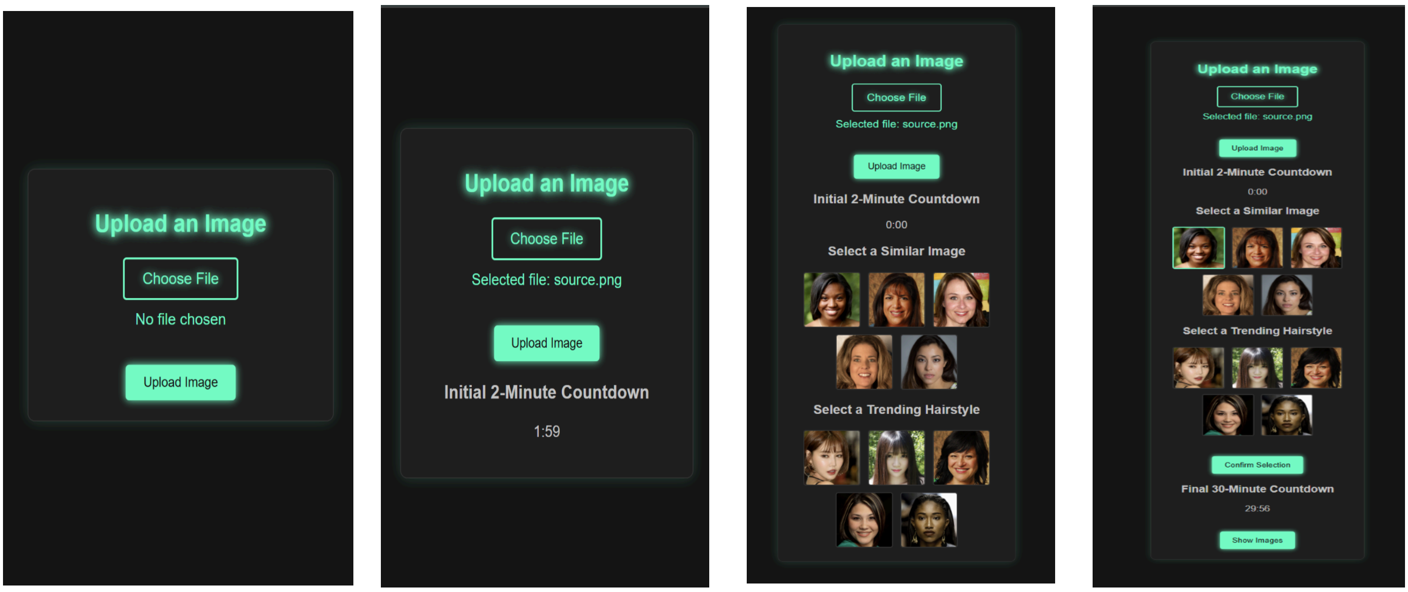


Fig 8.1 Web Application

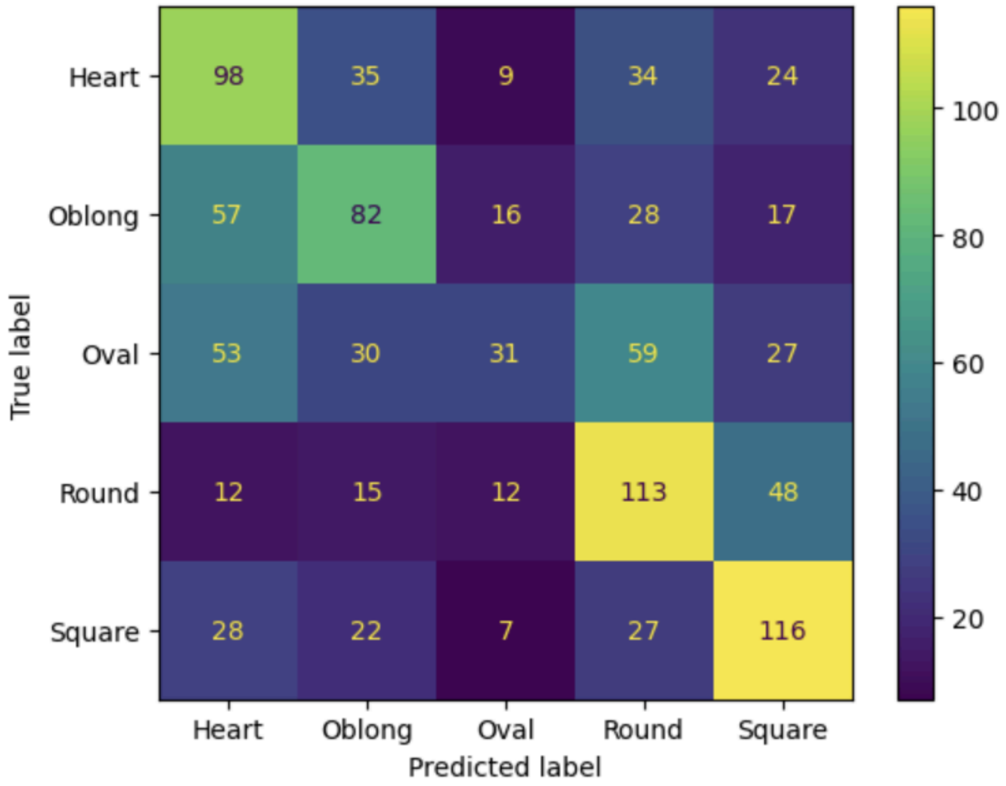


Fig 8.2 Confusion Matrix

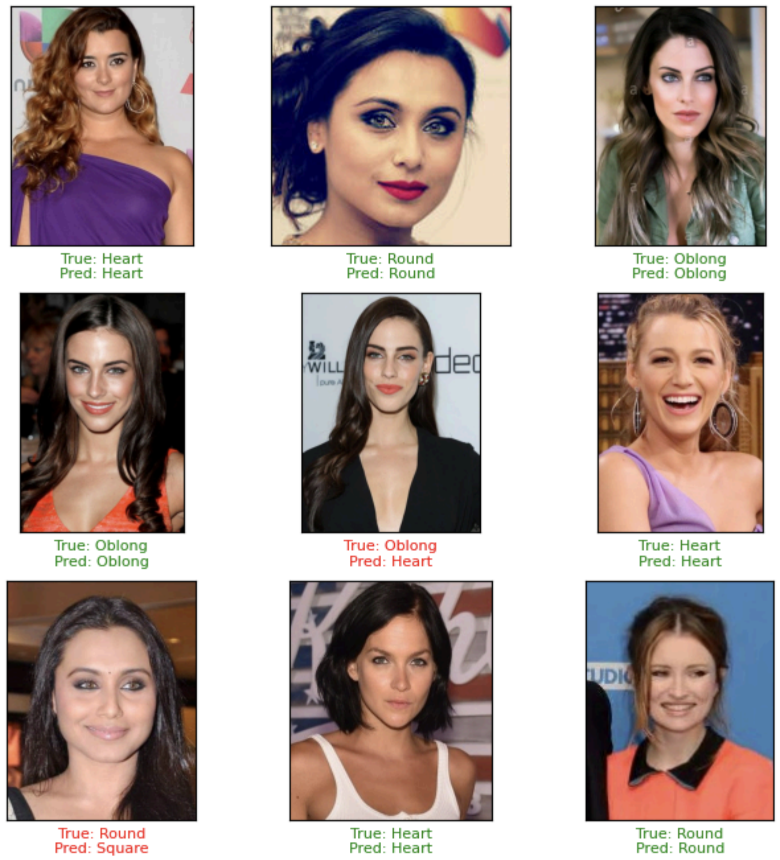


Fig 8.3 Validation results: Actual vs Predicted Face Shapes

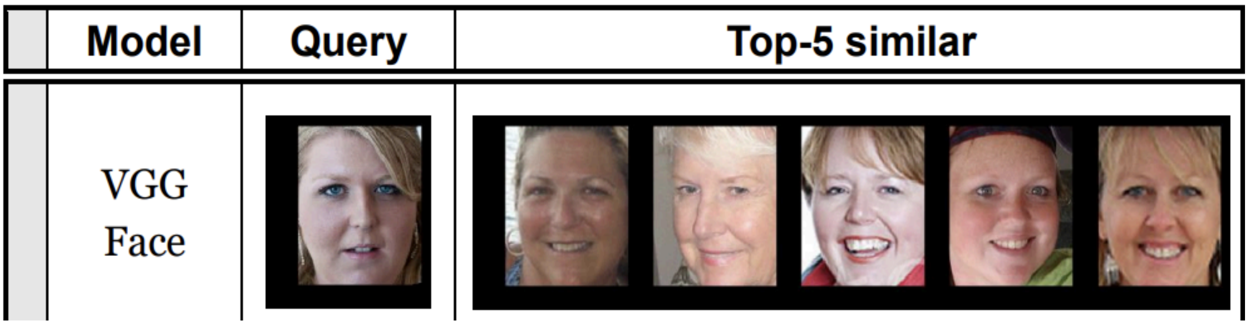


Fig 8.4 Similarity Analysis

Fig 8.5 Visual Results of Virtual Hair Transformation

CHAPTER 9

CONCLUSION AND FUTURE WORK

It combines an impeccable virtual try-on feature supplemented with personalized hairstyle recommendation based on AI-driven trend analysis. With the latest advancements in facial recognition and image processing, the application rests on very stable ground for such a construct. The next steps are accurate and time-efficient modeling, using advanced models, increasing the extension of the platform, and refining feedback-based recommendations. Real-time updates also ensure that the application will keep relevance alive and dynamic in terms of personalized style exploration.

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