Machine Learning Based Visual Style Advisor for Personalized Fashion and Beauty Recommendations

S.A.D.T. Prasadi
Department of Information Technology
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it21894824@my.sliit.lk

M.K.I. Vikasitha
Department of Information Technology
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it21180798@my.sliit.lk

D.R. Senarathne
Department of Information Technology
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it21180798@my.sliit.lk

J.H.M. Shaakir
Department of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
it21322280@my.sliit.lk

M. P. Gamage
Department of Computer Science and Software Engineering)
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
manori.g@sliit.lk

U. Dharmakeerthi
Department of Computer Systems and Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
uditha.d@sliit.lk

***Abstract*— The selection of haircuts, hair colors, clothing, and makeup is a significant challenge to many young individuals without the assistance of a professional. Fashion and beauty, although paramount in self-confidence and self-expression, become an issue if a precise plan of action is not designated. To alleviate this issue, this paper proposes a system named, "Machine Learning Based Visual Style Advisor for Personalized Fashion and Beauty Recommendations." The system customizes haircuts, hair colors, clothing, and makeup recommendations by taking facial features, personal attributes, and user-provided data as inputs. It utilizes deep learning, machine learning, and computer vision for automatic extraction of important features such as face shape, eye color, skin color, lip shape, eyebrow shape, and body type wherein the user has a particular style of interest. Realistic simulations allow users to see recommended haircuts and colors in advance, which improves decision-making. The system improves user experience and satisfaction by providing context aware recommendations which require less manual effort.**

Keywords*— *fashion and beauty, facial features, personalized recommendations, machine learning, computer vision

I. INTRODUCTION

The way fashion and beauty work has evolved thanks to digital technology, mostly when it comes to tailored suggestions. People now look for specific assistance on how to improve their appearance, from haircuts and hair colors to clothing and makeup. At the same time, due to numerous factors interrelated to gender, occasion, eye color, skin color, body type, lip shape, eyebrow shape, face shape and personal preferences determining which style is appropriate can be complicated. Some existing tools provide for virtual try-ons and style suggestions, but most do not consider the full range of an individual's unique features.

The main goal of personalized fashion and beauty recommendations is to aid people in choosing the best styling options. While some applications provide basic guidance to styles, they often require users to manually input personal traits like skin tone or face shape, which can be time-consuming and prone to errors. In addition, many systems that are trying to solve this problem do not consider how the values of many attributes interact. To solve this problem and give each user more accurate and powerful recommendations, technical assistance such as machine learning, deep learning, and computer vision is required.

As a solution, this research proposes a Machine Learning-Based Visual Style Advisor — a mobile application designed to automatically extract key features from a user's image, such as face shape, eye color, skin tone, lip shape, eyebrow shape, and body type. Besides, it will incorporate user-provided inputs such as personal preferences, gender and occasion to generate personalized recommendations.

The system intends to process user images using machine learning algorithms together with deep learning approaches to extract relevant features and recommend specific haircut, hair color and clothing and makeup recommendations. The addition of a virtual try-on feature will reduce the need for extensive manual input by allowing users to preview the recommended styles in real time. This not only enhances confidence in their style choices but also ensures a smooth and intuitive user experience.

This research brings multiple advantages to the users and will deliver precise custom recommendations for users which decreases their workload in finding matching appearances. User satisfaction improves through automatic physical attribute extraction which removes human errors involved in manual input tasks. User engagement will rise because of the real-time virtual try-on feature which creates an interactive way for users to select their style choices. This research is designed to offer better personalized suggestions for fashion and beauty, transform the industry and encourage more users to stick with it.

II. RELATED WORK

Research into personalized fashion and beauty recommendations that employ machine learning functions have limited existence despite their high day-to-day significance. The functions of fashion and beauty that help people express themselves and boost their confidence still lack sufficient implementation of machine learning for delivering individualized realistic recommendations. Current applications provide insufficient personalized experiences with real-time visualizations since they fail to address users with different preferences thus creating opportunities for development in this field.

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Using machine learning techniques is what has led to recent progress in customizing recommendations for users. The Random Forest Classifier applied by Patel et al. [1] could provide more accurate advice on clothes, but users had to fill in details by hand, so the algorithm wasn't fully automated. Wazarkar et al. [2] implemented Xception, a fancy deep learning model, that tracked shape details in the body and outperformed conventional machine learning models. As in the previous case, using VGG16 and ResNet for body shape classification in this study illustrates efforts to improve recognition by applying contemporary convolutional networks.

CNNs are powerful technologies used for identifying useful features and classifying data. Gunawansyah et al. [3] applied both CNNs and CBF for fashion recommendations, getting a 96.61% accuracy in their training by identifying different body shapes in photos. When the datasets are not large such as in Tio's [4] case in face shape classification, using transfer learning with Inception V3 is effective. This way, the process was automated so people didn't have to handle feature extraction manually.

Support Vector Machines (SVMs) have been applied in a number of different contexts. Sarraf [5] used SVMs for hair color classification. Unfortunately, SVMs did not handle very subtle colors well. The work of Sarraf involved a comparative study which showed that ensemble performed better than a single model by 8.3% in terms of accuracy, with the winning model being gradient boosting (like the 94.2 % accuracy). The work of Pasupa et al. [6] had the purpose of advancing the capabilities of SVMs by the use of Multiple Kernel Learning (MKL) for face shape, to which will create very effective classification accuracy in haircut recommendation situations.

Image processing methods have proven to be consequential tools for extracting details about the physical and facial capture. Borza et al. [7] provided an accuracy of 92% for hair segmentation with a type of deep learning approach, but the cost was computationally expensive. Reported the use of state of the art methods of segmentation which can extract the color data from photographs and faces and allow for further analysis in terms of the hair attributes, which gave an accuracy of 91.2 % to hair colour although the authors suffered a range of lighting issues and complex hairstyles. Ileni et al. [8] made some improvements that effectly reduced processing time by 40% and still maintain an accuracy of 89%.

Yoon et al. [9] developed Mobile-UNET which they proposed for real-time problems since it is a light architecture that accurately detects objects. You can use this tool in real-time, as it is very accurate (89.3%) and efficient (150ms on typical mobile devices). They managed to lower the number of parameters by 73% in their network without losing accuracy.

Alzahrani et al. [10] validated that mixing CNNs with manually designed features adds to CNNs' resistance to different lighting conditions in recognizing faces. They combined handcrafted features and Inception V3 to build a set of models for advising hairstyles, maintaining a steady performance no matter the circumstances. Identification of the shapes of various regions on the face was also made possible by their method which used Dlib and checked for facial landmarks [11]. For face detection, they applied the Haar Cascade approach and for marking landmarks, they relied on Dlib. Their hairstyle suggestion platform was able to correctly classify face shapes into five categories with an accuracy level of 85%.

Many benefits for the user are provided by Augmented Reality (AR) technology. A 3D face-tracking system for virtual hair was developed by Tang et al. [12] that displays hair colors in real time. In their studies, the system finished with a user satisfaction rate of 87%, much higher than the 63% satisfaction from other kinds of systems.

Transforming colors using HSV has been found useful, with Lee et al. [13] asserting that it leads to better color matching accuracy than the common RGB solution for hair color analysis by around 12%. In doing so, their platforms used cognitive knowledge-based systems, leading to an increase in user satisfaction by 17%.

Advanced types of ensembles have succeeded in different recommendation areas. Because of higher accuracy, strong robustness and the ability to deal with complex data, XGBoost, discussed by Chen and Guestrin [14], has become popular and is well-suited for recommending makeup. It is in line with Weerasinghe and Vidanagama [15], whose hair color recommendation machine learning model using Decision Trees scored 77% user approval. Besides, Doshi et al. [16] proved that applying Random Forests improved the effectiveness of customization by 14%. By combining recognition of the face and hair in their recommendation system, they managed to optimize it by using both machine-based and self-provided features.

Using clustering techniques, researchers are able to perform both segmentation and classification duties. To support different skin tones, Reference [17] used the K-means algorithm to identify users' skin tones in their fashion recommender system. By using this technique, traditional recommendation systems were able to give greater importance to this specific form of personalization.

People are now paying more attention to generative models as they make virtual try-on systems much more realistic. Using multi-view optimization and GANs, Khwanmuang et al. [18] introduced StyleGAN Salon for swapping hairstyles between photos with different poses. The method improved the realism in simulating hairstyle changes in images with varied poses.

Advancements in these systems have greatly depended on the development of datasets. Chen et al. [19] introduced a new dataset called CelebHair built from CelebA using facial landmarks and deep learning to extract features such as those for nose size and pupil distance. To deal with biases in makeup recommendation systems, some researchers have used the Synthetic Minority Over-sampling Technique (SMOTE).

UI and visualization technologies have greatly affected how widely technologies are adopted. Perera et al. [21] confirmed that using real-time coloring in the program increased users' satisfaction by 85%, but correcting the color for various types of hair remained problematic. Old ways of basing makeup on specific face features have shifted to rely more on information gathered using data. Liu et al. proposed a beauty advisor system that considers facial features when recommending make-up [22]. They review facial characteristics and different surroundings to give tailor-made advice using information gathered from many examples. Expert system developer Kim et al. [23], together with machine learning, introduced a more customized system for advising on makeup recommendations based on face features.

III. Methodology

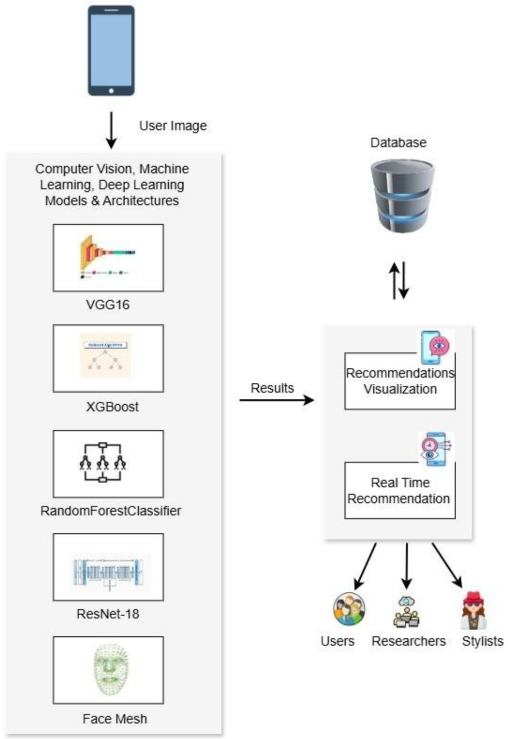


Fig. 1. Overall system diagram of the proposed solution

The proposed system is a mobile application that utilizes multiple components that will be discussed below to analyze users and provide recommendations and simulations for haircuts, hair colors, clothing, and makeup. As depicted in Fig. 1, the system detects the registered user's face and body once the user allows the application to use their mobile camera. It then extracts key attributes such as body type, skin tone, eye color, face shape, eyebrow shape, and lip shape and the user have the option to select gender, personal preferences and select the type of occasion they are planning for. These selected preferences, combined with the extracted personal attributes, are processed to generate tailored recommendations. Users can then utilize the application to try on and simulate the recommended haircuts and hair colors in real-time and visualize clothing and makeup.

A. Hair Color Recommendation

The hair color recommendation system addresses the challenge of selecting suitable hair colors by analyzing five key user characteristics: eye color, skin color, hair type, gender, and occasion. Real-time recommendations are provided through advanced image processing techniques applied to user images. The dataset shown in Fig. 2 includes eye color (Blue, Hazel, Green, Brown, Gray, Black), gender (Male, Female), hair type (Straight, Curly, Wavy, Kinky), occasion (Formal, Casual, Party, Sport), skin color (Tan, Dark, Fair, Medium), and the recommended hair color. This dataset was aggregated from Kaggle, beauty forums, and beauty care websites. For model evaluation, the data was split into 80% for training and 20% for testing. For preprocessing, we employ LabelEncoder for categorical variables and SMOTE to balance underrepresented hair color classes. Numerical features are normalized using StandardScaler, with StratifiedKFold ensuring robust cross-validation across both training and testing sets. User images are efficiently handled through Base64 encoding, enabling secure transmission via RESTful APIs without server-side storage requirements.

For accurate hair region extraction, we implement a ResNet-18 architecture trained on our 80% training split specifically for hair segmentation. The model achieves precise hair masking by leveraging deep residual learning, with preprocessing steps including normalization and augmentation applied only to the training data to prevent data leakage. The system employs MediaPipe Face Mesh's pretrained model for comprehensive facial landmark detection, specifically targeting the eye region for eye color extraction and cheek areas for skin tone analysis. Color extraction performed through K-Means clustering in LAB color space using OpenCV to identify dominant colors in the segmented eye and skin regions. These extracted visual features are systematically integrated with user-provided attributes (hair type, gender, and occasion) through rule-based deduction logic, creating comprehensive interaction features (e.g., Skin_Hair_Type, Eye_Gender combinations) that form the complete feature set for the XGBoost recommendation model.

The recommendation engine uses XGBoost trained on the 80% training portion with optimized hyperparameters (max_depth=10, learning_rate=0.03, lambda=1.5) for the multi-class problem using the "mlogloss" objective with early stopping. The XGBoost model processes the merged feature set—combining MediaPipe-extracted visual features with user characteristics—to generate personalized hair color recommendations through sophisticated gradient boosting algorithms. The model's performance was rigorously evaluated on the held-out 20% testing set, achieving exceptional results shown in Fig. 3 with 100% validation accuracy and perfect precision/recall across all hair color categories. For real-time application, users can instantly apply the recommended hair color through our integrated visualization system: the segmented hair region from ResNet-18 undergoes color transformation using the XGBoost-recommended shade, then seamlessly blends with the original image through alpha compositing in OpenCV, providing users with photorealistic previews of their potential new looks in real-time.

```
[27]
... Drive already mounted at /content/drive; to attempt to forcibly remount, call driv
    Dataset Head:
      eye_color  gender hair_type occasion skin_color hair_color_recommendation
    0      Blue  Female  Straight   Formal        Tan                Ash Blonde
    1      Blue  Female  Straight   Casual       Dark                Dark Brown
    2     Hazel    Male     Curly    Party        Tan                Dark Brown
    3     Hazel    Male  Straight    Party       Fair                Copper Red
    4      Blue    Male     Curly    Sport     Medium             Violet Purple
```

Fig. 2. Dataset head

Model	Architecture	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Time (h)
XGBoost	max_depth=10, lr=0.03	100.0	100.0	100.0	1.00	4.2
Random Forest	n_estimators=100	94.3	93.8	94.1	0.94	2.8
Neural Network	3 layers, 512 units	95.7	95.2	95.5	0.95	6.5
SVM	RBF kernel	89.2	88.7	89.0	0.89	1.9

Fig. 3. Comparison of hair color recommendation models

TABLE I. COMPARISON OF SELECTED ARCHITECTURES FOR HAIR SEGMENTATION

Architecture	IoU Score
ResNet-18	95.2
U-Net	92.5
DeepLabV3	93.8

B. Hair Cut Recommendation

This work substantially approaches building an intelligent haircut recommendation system based on machine learning using a systematic research methodology. The system suggests haircuts best suitable for end users based on their gender, face shape, hair type, and occasions. Through the developmental process, data collection, preprocessing, model selection, portrait face shape detection, back end deployment, and the implemented frontend take place. Each step sports a crucial part to offer precision efficiency in the system operation. The dataset in this research was collected from various online sources, including hairstyle websites and beauty forums. The data is labeled examples of different haircuts and contains user attributes, such as gender, face shape, hair type, and looktype. Per the nature of raw datasets, many of them might contain missing or contradictory values; therefore, it is necessary to perform data preprocessing, which consists of cleaning and refining the data before they are injected into the machine learning model. Missing values of categorical attributes were replaced by the frequently occurring category, while numeric attributes were normalized for consistent scale.

SMOTE was subsequently applied in order to generate new samples to represent underrepresented classes, to assure balance across haircut types with respect to the face shape. The next step was to detect the user's face shape, which is a major factor in choosing haircuts. This was done with Mediapipe's FaceMesh, a deep learning-based framework for facial landmark extraction. Once the user uploaded an image, the system would collect the captured images and preprocess them using OpenCV's rescale and grayscale. Mediapipe then locates prominent features on the face such as the width of the jaw, the width of the cheekbone, the width of the forehead, and the height of the face. Five face shapes were predefined and classified based on these measurements: Round, Oval, Square, Heart, and Diamond. Comparison with regard to the proportionality of these facial features leads to an exact face shape classification.

For haircut recommendations, XGBoost, an optimized gradient boosting algorithm that is efficient and provides accurate prediction, was implemented to build a machine learning model. The model was trained on a preprocessed dataset, which had input features of gender, face shape, hair type, and occasion, where the target variable was the category of haircut. By tuning key hyperparameters-n_estimators, max_depth, learning_rate, and subsample-their overall effect on performance was improved. In evaluating the performance and generalization ability of the model, the dataset was divided into training and testing subsets in the proportion of 80 to 20%, respectively. Model performance was viewed in terms of classification report, confusion matrix, and accuracy score. The model has been integrated into a FLASK-based backend for deployment purposes. The trained XGBoost model and label encoders were stored with joblib, loaded into the Flask API, and served user requests. Once the backend gets User attributes via a REST API, the input is processed before returning the most relevant haircut recommendation.

C. Clothing Recommendation

The system uses the VGG-16 model, a deep convolutional neural network known for its superior performance in picture classification tasks, to classify skin tones. VGG-16 was chosen because of its capacity to capture detailed details and minor color fluctuations, making it an excellent tool for determining skin tone. To improve accuracy, OpenCV is used for image preprocessing. OpenCV initially loads a pre-trained Haar Cascade classifier for face detection, which is then converted to grayscale to boost detection accuracy. The system recognizes faces in images and separates dominant skin regions. The model then determines the user's skin tone, which is used to recommend clothing colors that best complement.

For body type classification, the system uses a Random Forest Classifier (RFC), an ensemble learning method that builds numerous decision trees and blends their outputs to increase accuracy. RFC was chosen for its capacity to handle high-dimensional data while reducing overfitting, making it ideal for identifying body shapes. The model is trained on Newcastle University's Human Body Shape Classification Dataset, which includes identified body shapes as well as associated body measures including front bust, front waist, front hips, and height. When the user uploads an image, the system extracts body measurements through image processing. The trained RFC model analyzes these measurements to accurately predict the user's body type.

Once the skin tone and body type have been identified, the system combines these predictions with the user-provided gender and occasion details to generate personalized clothing recommendations. The final output is retrieved from Open AI, ensuring that the displayed outfits align with the user's style preferences and event requirements.

D. Makeup Recommendation

Facial makeup recommendation is a growing field that applies machine learning techniques to deliver personalized beauty suggestions based on both facial features and user-defined preferences. In the proposed system, a pre-trained MediaPipe Face Mesh model is used to extract two specific facial attributes: lip shape and eyebrow shape. Landmark points are analyzed using geometric ratios such as width, height, and symmetry to classify lips into Full, Thin, Round, or Wide, and eyebrows into Thick, Thin, Arched, or Flat.

These extracted features are combined with additional user inputs, including skin tone, eye color, hair type, preferred look type, and occasion, to build a comprehensive input set. An XGBoost classifier, known for its accuracy and efficiency in handling structured data, is used to predict the most appropriate makeup look. The model is trained on a curated dataset and evaluated using performance metrics like a confusion matrix and feature importance analysis to ensure reliable results.

The final output consists of three elements: a named makeup look (e.g., Elegant Look), a detailed textual description providing tailored suggestions for foundation, eyes, lips, cheekbones, and nose, and a sample reference image representing the recommended style. The system does not apply makeup in real time or overlay it on the user’s image. Instead, it delivers an informed recommendation based on facial geometry and context, ensuring both practicality and scalability for beauty advice.

IV. RESULTS AND DISCUSSION

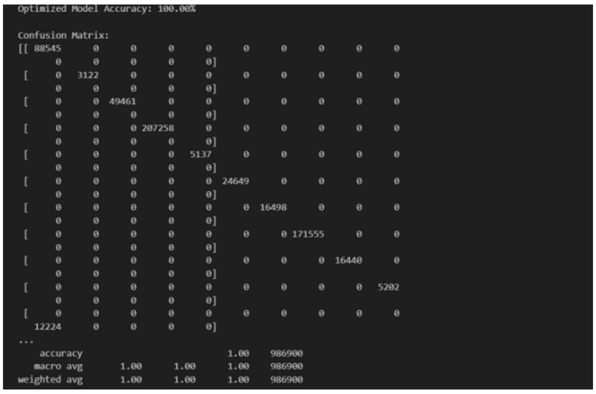
In this section, the results of the proposed system are discussed. The integrated hair color recommendation system successfully combines several advanced techniques to enhance accuracy and personalization. MediaPipe Face Mesh effectively detects precise facial landmarks, which allows accurate extraction of skin and eye regions. These regions are then processed using OpenCV for color space conversion and enhanced image manipulation, ensuring consistent inputs across different lighting conditions. K-Means Clustering identifies dominant skin and eye colors from the extracted regions, providing reliable features for the recommendation engine. For hair segmentation, the ResNet18 model isolates hair regions, ensuring irrelevant parts do not affect color recommendationsThe extracted features are then used in an XGBoost model, as shown in Fig. 4, achieving 100% accuracy by leveraging SMOTE for class balance and fine-tuned hyperparameters. Similarly, the haircut recommendation model, trained over 10 epochs using XGBoost and SMOTE, utilized user features such as gender, face shape, and style preferences to achieve over 90% accuracy, as shown in Fig. 6, demonstrating strong generalization across diverse profiles. This fusion of computer vision and machine learning components demonstrates a robust, scalable solution for real-time, user-personalized hair color suggestions, laying a foundation for potential expansion into more diverse and inclusive datasets.

The makeup recommendation component successfully achieves personalized suggestions based on facial features, specifically focusing on lip shape and eyebrow shape extracted using the Mediapipe Face Mesh model. These features, along with additional contextual inputs like skin tone, eye color, hair type, occasion, and look type, are used to generate accurate and detailed makeup recommendations through an XGBoost classifier. The trained model demonstrated strong performance, achieving over 95% accuracy on the test dataset, indicating reliable prediction capabilities. The confusion matrix and classification report shown in Fig. 7 confirmed that the model maintains consistency across all makeup classes, including Bold Glam, Classic Professional, Edgy Look, Smokey Eye Makeup, and others. As an output, the system generates a makeup look name, displays a reference image representing that style, and presents a feature-based description that includes suggestions for eyeliner, eyeshadow, foundation, lips, cheekbones, and nose makeup. For example, a predicted output like “Smokey Eye Makeup” is accompanied by a description such as “dark eyeliner and eyeshadow with bold contouring and matte foundation,” ensuring the recommendation is both informative and practical.

The body type classification model achieved an overall accuracy of 87.5%, with a weighted average F1-score of 0.87, demonstrating strong and consistent performance across all classes. Effective classification of body types is shown by the precision and recall values, giving F1-scores of 0.80, 0.86 and 1.00 for each category. Each class had an equal number of samples in the test set which helped to produce better evaluation metrics. Despite this, the relatively small dataset size remains a limitation, potentially affecting the model’s ability to generalize to a wider range of body shapes. Additionally, the current classification is restricted to three broad categories, such as tall, slim, and average which may not fully capture the diversity of human body types. Future work will focus on expanding the dataset, introducing more specific body shape labels, and automating gender detection to enhance the system’s accuracy, personalization, and overall usability.

TABLE II. COMPARISON OF SELECTED ARCHITECTURES FOR HAIR SEGMENTATION

Recommendation Model	Final Validation Accuracy
Hair Color Recommendation	100%
Hair Cut Recommendation	96%
Makeup Recommendation	99.99%
Clothing Recommendation	87.5%



```
Optimized Model Accuracy: 100.00%

Confusion Matrix:
[[ 88545      0      0      0      0      0      0      0      0      0
       0      0      0      0      0]
 [     0   3122      0      0      0      0      0      0      0      0
       0      0      0      0      0]
 [     0      0  49461      0      0      0      0      0      0      0
       0      0      0      0      0]
 [     0      0      0 207258      0      0      0      0      0      0
       0      0      0      0      0]
 [     0      0      0      0   5137      0      0      0      0      0
       0      0      0      0      0]
 [     0      0      0      0      0  24649      0      0      0      0
       0      0      0      0      0]
 [     0      0      0      0      0      0  16498      0      0      0
       0      0      0      0      0]
 [     0      0      0      0      0      0      0 171555      0      0
       0      0      0      0      0]
 [     0      0      0      0      0      0      0      0  16440      0
       0      0      0      0      0]
 [     0      0      0      0      0      0      0      0      0   5202
       0      0      0      0      0]
 [     0      0      0      0      0      0      0      0      0      0
   12224      0      0      0      0]
...
    accuracy                          1.00    986900
   macro avg       1.00      1.00      1.00    986900
weighted avg       1.00      1.00      1.00    986900
```

Fig. 4. Model performance evaluation of hair color recommendation: confusion matrix and metrics

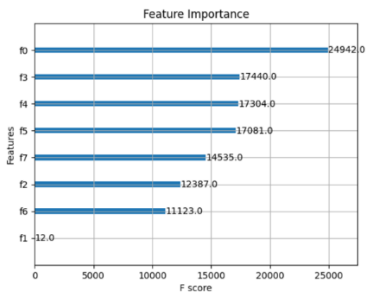
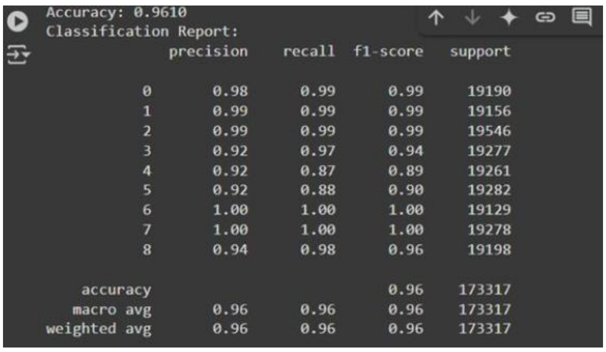


Fig. 5. Features work with labels in hair color recommendation model

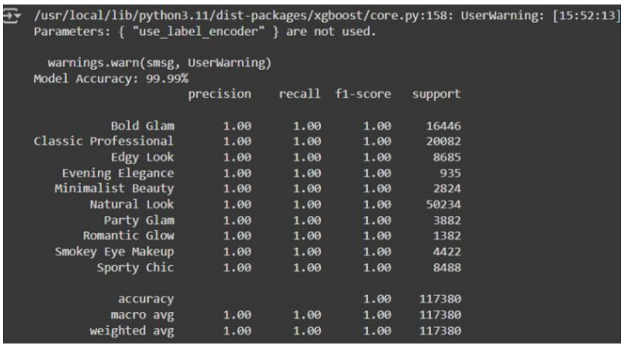


```
Accuracy: 0.9610
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.99     19190
           1       0.99      0.99      0.99     19156
           2       0.99      0.99      0.99     19546
           3       0.92      0.97      0.94     19277
           4       0.92      0.87      0.89     19261
           5       0.92      0.88      0.90     19282
           6       1.00      1.00      1.00     19129
           7       1.00      1.00      1.00     19278
           8       0.94      0.98      0.96     19198

    accuracy                           0.96    173317
   macro avg       0.96      0.96      0.96    173317
weighted avg       0.96      0.96      0.96    173317
```

Fig. 6. Classification report of the hair cut recommendation model



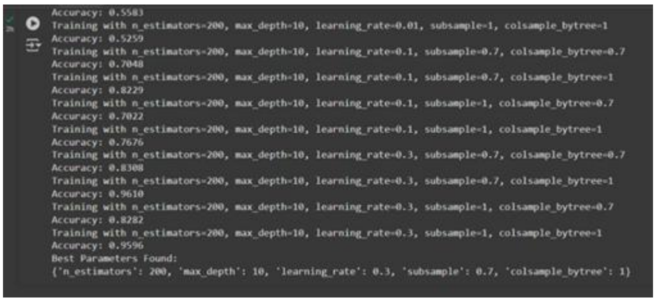
```
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [15:52:13]
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
Model Accuracy: 99.99%
                      precision    recall  f1-score   support

           Bold Glam       1.00      1.00      1.00     16446
Classic Professional       1.00      1.00      1.00     20082
           Edgy Look       1.00      1.00      1.00      8685
     Evening Elegance       1.00      1.00      1.00       935
    Minimalist Beauty       1.00      1.00      1.00      2824
        Natural Look       1.00      1.00      1.00     50234
          Party Glam       1.00      1.00      1.00      3882
        Romantic Glow       1.00      1.00      1.00      1382
   Smokey Eye Makeup       1.00      1.00      1.00      4422
         Sporty Chic       1.00      1.00      1.00      8488

            accuracy                           1.00    117380
           macro avg       1.00      1.00      1.00    117380
        weighted avg       1.00      1.00      1.00    117380
```

Fig. 7. Classification report of the makeup recommendation model



```
Accuracy: 0.5583
Training with n_estimators=200, max_depth=10, learning_rate=0.01, subsample=1, colsample_bytree=1
Accuracy: 0.5259
Training with n_estimators=200, max_depth=10, learning_rate=0.1, subsample=0.7, colsample_bytree=0.7
Accuracy: 0.7048
Training with n_estimators=200, max_depth=10, learning_rate=0.1, subsample=0.7, colsample_bytree=1
Accuracy: 0.8229
Training with n_estimators=200, max_depth=10, learning_rate=0.1, subsample=1, colsample_bytree=0.7
Accuracy: 0.7022
Training with n_estimators=200, max_depth=10, learning_rate=0.1, subsample=1, colsample_bytree=1
Accuracy: 0.7676
Training with n_estimators=200, max_depth=10, learning_rate=0.3, subsample=0.7, colsample_bytree=0.7
Accuracy: 0.8308
Training with n_estimators=200, max_depth=10, learning_rate=0.3, subsample=0.7, colsample_bytree=1
Accuracy: 0.9610
Training with n_estimators=200, max_depth=10, learning_rate=0.3, subsample=1, colsample_bytree=0.7
Accuracy: 0.8282
Training with n_estimators=200, max_depth=10, learning_rate=0.3, subsample=1, colsample_bytree=1
Accuracy: 0.9596
Best Parameters Found:
{'n_estimators': 200, 'max_depth': 10, 'learning_rate': 0.3, 'subsample': 0.7, 'colsample_bytree': 1}
```

Fig. 8. Training accuracy with 10 epochs

V. CONCLUSION AND FUTURE WORK

In this paper, a Machine Learning-Based Visual Style Advisor for Personalized Fashion and Beauty Recommendations is proposed. The purpose of this research is to generate personalized fashion and beauty recommendations for users of the application. Automatic extraction of facial and bodily features such as hair type, face shape, skin tone, eye color, body type, eyebrow shape, and lip shape, combined with user-provided inputs such as gender, occasion and personal preferences are employed to generate tailored recommendations. Users can see their new look through real-time simulations featuring suggested haircut and hair color. This system has the potential for great improvements in the future. Directions for future work include incorporating further improvements such as enhancing the real-time simulation feature to include clothing and makeup, improving the user interface and user experience of the mobile application and adding features such as style trends, seasonal recommendations, and social sharing options to make the application more engaging and interactive.

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