

Perfect Eye Makeup by AI: Style Based on Your Eye Shape

M.Soundarya
department of Information Technology
Velammal College of Engineering and
Technology
Madurai, India
soundaryajeyaraj5@gmail.com

M.Praseetha
department of Information Technology
Velammal College of Engineering and
Technology
Madurai, India
madhuprase@gmail.com

Poorna Devi K G
department of Information Technology
Velammal College of Engineering and
Technology
Madurai, India
poornadevikg@gmail.com

Abstract-Artificial intelligence (AI) continues to transform the beauty and cosmetic industry by enabling customized recommendations and automated analysis. This paper presents an eye image categorization and makeup recommendation system built using deep learning based on the YOLOv8 model. A private dataset of male and female eye images was preprocessed and split into training and validation sets for equitable learning. The YOLOv8 classifier was trained to distinguish between categories of eyes with precise consistency, as context-aware makeup recommendations' foundation. In addition to categorization, the system incorporates a built-in rule-based recommendation component that provides two forms of personalization: generalized makeup styling recommendations based on gender-specific eye features, and eyeshadow color suggestions as a function of user-provided skin tone indicators (fair, medium, or deep). Two-stage use of computer vision and cosmetics expertise generates more significant and user-friendly suggestions compared to conventional static approaches. The proposed system has application in virtual beauty assistants, web shops, and mobile applications, offering scalable and responsive solutions for enhanced customer interaction. By integrating AI-based classification and cosmetic domain expertise, this study underscores the growing presence of intelligent systems in the work of personalized beauty technology.

Keywords Convolutional Neural Networks (CNNs), Deep Learning, YOLOv8 Classifier, Image-based Feature Extraction, Artificial Intelligence in Cosmetics

I. INTRODUCTION

Eye makeup is among the modern beauty trends, cosmetic and social. Eye makeup provides facial proportion, delineates eyes, and is an expression of personal taste. With advancements in technology in the beauty industry, there has been a high focus on integrating artificial intelligence (AI) in providing personalized makeup advice due to the individual features of individuals' faces. This article suggests an AI-powered tool offering customized eye makeup tips based on looking at the shape of your eyes. The system utilizes computer vision techniques to extract geometric characteristics of the images of the eyes, including width-to-height ratio, apparent crease visibility, outer corner angle, and interocular distance.

Upon classification, the system suggests suitable eye makeup methods, such as eyeliner application, eyeshadow positioning, and blending methods that suit the determined shape. In order to facilitate this system, a labeled dataset of eye images and expert guidelines on makeup was constructed. The model proposed demonstrates the capability of AI to provide user-oriented beauty suggestions, offering a novel mechanism to enhance makeup routines through automation and customization.

II. LITERATURE SURVEY

several research studies have aimed at creating AI driven beauty and facial analysis systems that employ different techniques in image processing, classification, and recommendation generation. The studies differ in their data source, feature extraction, and application domains. This section summarizes the relevant works that guided the design and development of our personalized eye makeup recommendation system.

[1] Bhat et al. designed an eye contour detection scheme from the Active Shape Model (ASM) for accurate boundary positioning of face images. Their scheme showed good detection of eyelid shape curvature and eye shape geometry, leading to better facial feature extraction. The scheme was not real-time-capable, however, constraining its potential use to static image processing. And also, the system did not entail providing personalized makeup advice or interactive user feedback. With these considerations in mind, their effort is still worth the trouble as a foundation for contour-based eye understanding in computer vision. From a geometric modeling perspective, the work opened the door to incorporating structural eye understanding into cosmetic guidance systems to be developed in the future.

[2] Alzahrani et al. implemented the rule-based geometric eye shape categorization to strong classes. The process categorized eye shapes with regard to geometric properties like aspect ratios, curvature, and angular orientation. The system categorised eye shapes into strong classes efficiently using systematic ocular variations descriptions. Although precise, the procedure was tainted by pre-specified geometric rules and therefore had limited adaptability in most facial expressions. Secondly, the system was not interactive and personalized in terms of beautification suggestions. That is, this paper provided an appropriate groundwork in the shape recognition and eye classification form and hence a milestone for future system integration of AI-based personalization.

[3] Nishimura and his crew developed a makeup system that converts reference images into usable eye designs. Everyone didn't have to possess any professional training—once the design was printed on transfer sheets, they could apply it immediately and receive a detailed appearance. The entire concept was to make it simple so anyone could use it. Rather than providing personal beauty advice or suggestions, the system emphasized style and creativity. Their research demonstrated that technology has the ability to enable artistic makeup for common users by allowing them to replicate designs, instead of depending on typical beauty categories or recommendations.

[4] Alzahrani et al. subsequently furthered their work by proposing a multi-model system blending hybrid handcrafted features with deep learning using CNN. This system made both facial and ocular attribute classifications to offer rule-based, automated beauty guidance recommendations, for example, hairstyles and eyelashes. The hybrid method was more robust than exclusively geometric or CNN-based systems but was constrained by a rule-based recommendation aspect, preventing adaptability to personal aesthetic tastes. In spite of this, the framework symbolized a significant move towards complete AI driven beauty assessment. By coupling classification with actionable recommendations, it bridged the gap between technical image analysis and real-world consumer usage.

[5] Jiang et al. introduced an expert-designed rule-based system for facial makeup recommendation through facial attribute classification and digital generation. The system builds realistic makeup recommendations for particular events with semantic descriptions to achieve higher transparency. The transparency mechanism enhanced user trust and engagement by attaining reasoning transparency behind the suggestions. User feedback was also utilized for justification and enrichment of system output. Even though it did function, the system could not manage very creative and personalized ideas of beauty. However, it showed the promise of being able to integrate the expertise knowledge with the AI so that it can generate realistic, authentic, and customer-driven concepts of beauty.

[6] Jeamsinkul developed Masque Array, an automatic cosmetic selector and applicator system that attempted to couple face scanning with rule-based recommendation. The system offered rapid, personalized, and secure cosmetic application that allowed realistic results tailored to individual consumers. In contrast to previous classification-based studies, Masque Array bridged the gap to real-world usage by easing selection and physical application. Safety and simplicity were prioritized, allowing it to break into a wide range of consumer groups. Though dependent upon pre-programmed rules, it was restrained from fitting individual personal styles to a high extent. Nevertheless, the system was a huge leap forward in automatic beauty technology that filled the gap between AI analysis and hands-on applications.

[7] Adams showcased an industry sector overview of innovations highlighted at the Color Cosmetics Conference such as pigment science, color measurement, and optical effects for eye makeup products. The overview highlighted technological advancements in mascaras, eyeliners, and eyeshadows in enhancing durability and beauty quality. Interpreting the advancements in material science in terms of user experience, the overview connected industrial research to potential AI-enabled personalization means. Thus, it provides timely insight into putting AI-based beauty apps in global product development trends.

[8] Florea suggested a classification method for HSV histogram-based classification of eye colors employing Support Vector Machines (SVMs). The method employed accurate classification of eye color employing color-space translation in the attainment of discriminative information. The method was focused on improving cosmetic recommendation systems through the delivery of satisfactory makeup suggestions over natural pigmentation of the eyes. Customization recommendation in attaining aesthetic compatibility was the focus of research. Global face-related characteristics and active interaction were not recovered by model, shortening its scope of applicability. Even with the above limitations, the book greatly enhanced application of custom-made-cosmetic suggestions based on color-based analysis.

[9] Orlosky et al. developed Eye Shadows, a point-of-gaze AR/VR selection technique founded on peripheral virtual shadows of objects for enhanced and faster user interaction. Their system reduces visual clutter, avoids the "Midas touch" problem, and preserves central vision while enhancing analog control in immersive environments. Comparative studies showed that Eye Shadows achieved higher selection accuracy and speed compared to traditional dwell-based gaze methods. While not a direct makeup recommendation system, it demonstrated the potential of gaze tracking for interactive beauty applications in AR/VR. This contribution highlights a pathway for future cosmetic systems that integrate real-time gaze-based personalization.

[10] Mangtani examined the revolutionary effect of AR and AI technologies on the beauty sector, particularly in the post-COVID-19 setting. The study covered the manner in which virtual try-ons, customized skincare mechanisms, and AI-based beauty recommendations satisfy hygiene needs and shifting consumer trends. AR-enabled try-on capabilities allow users to try out makeup styles in contact-free, safe methods, and AI enhances customization and consumer happiness. The research also highlighted industry adjustment to digital-first campaigns in order to continue engagement in socially distanced settings. Sweeping in its reach as it is, the study underscores the value of AI and AR to produce secure, innovative, and personalized make-up experiences.

[11] Pazhoohi and Kingstone had assessed how much eyelash length is associated with perceived attractiveness in various groups of races. An inverted-U shape was discovered, which had most beautiful eyelash lengths at a little over one-third of the width of the eye. This shape occurred in Asian, Black, Indian, and White faces, suggesting an evolutionary universal preference for proportional eyelash size. The research added valuable insights to aesthetic perception as well as to eyelash styling in makeup advice. It emphasized the interface of cosmetic practice and evolutionary psychology.

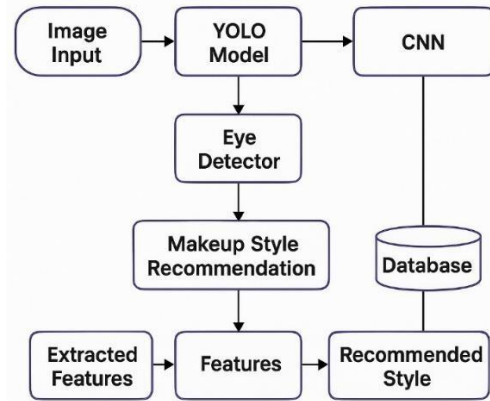
[12] Lee and Han used survey study with 448 Korean women attempting to research eyelash extension and false eyelash preference and satisfaction. Results indicated participants preferred eyelash extensions over false lashes in terms of more natural appearance, comfort, and longevity. Black color, silk quality, JC-curl, 11 mm length, and 80% density were the preferred items. Greater satisfaction with extensions for both beauty and use This research targeted consumer-driven facet of cosmetic product development and selection.

[13] Gelneyeliner was tested by consumers under the control of Gedik, and it was also tested under conditions of daily use against cosmetic products. Gel eyeliner surpassed other types in wearability, stability, and usability. Consumer irritation, i.e., redness and irritation, was low, indicating potential safety issues. The result was products that may provide performance and comfort simultaneously were needed. Although not AI-influenced, the value that has been generated by the study is the same as its consumer insight and safety value in the case of eyeshadow.

[14] Eaton and Parry addressed the cultural relevance and health concern of kohl, an early eye shadow of universal and widespread use by many groups over time. In it, they spoke of widespread, worldwide use of kohl, especially among immigrant communities, as an identifier and marker of heritage. Richly meaningful, the product was extremely lead-contaminated, and there existed a health concern. This two-dimensional view pitted consumer health conflict against cultural heritage. It is with respect to AI-based recommendatory systems that a research spotlights the culture and safety burden issues. It puts things into perspective as to why cosmetic treatments kept innovating.

[15] Nakatsu et al. designed a fuzzy preference rule-based personalized makeup system and interactive evolutionary computation. It creates makeup styles and learns the user progressively with the assistance of feedback learning and incrementally evolutionary computation. Although it required more time than fully automatic methods, it was more satisfactory to users and nearer to personal taste aesthetically. The study proved that the synergy between human interaction and computer intelligence could generate extremely customized solutions to beauty. While reduced interaction rates, attention based on individual preference made the system extremely efficient in niche personalization. Overall, the study aimed for the role of adaptive learning in making user-oriented cosmetic technology.

III.ARICHITECTURE DIAGRAM



IV.PROPOSED WORK

The following section describes the methodology of the suggested system, intended for real-time eye makeup detection and recommendation. The system detects the user's eye region, categorizes the eye shape, and recommends an optimal makeup style. It also provides a virtual preview by virtually applying the suggested makeup style to the user's photo.

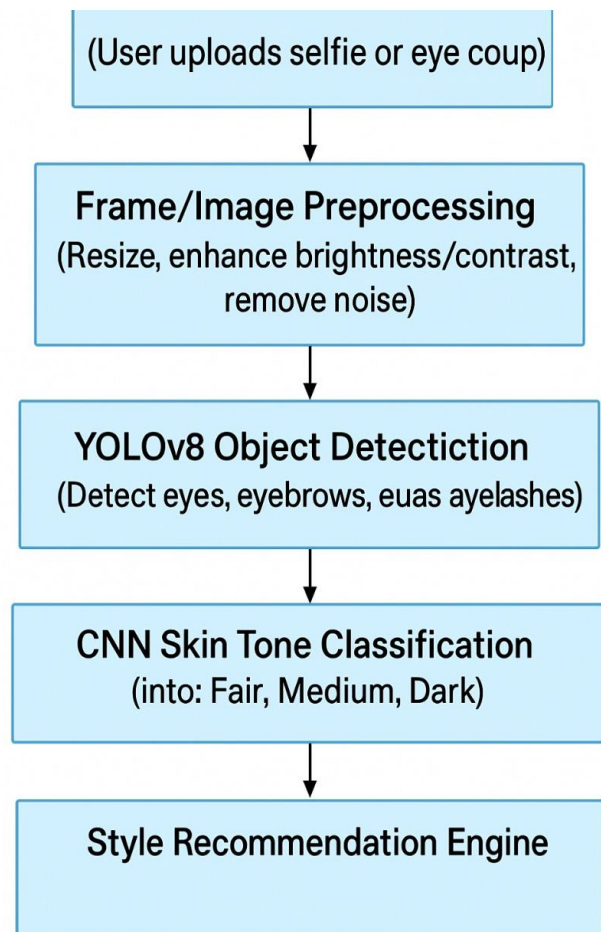


Figure1:Workflow of the AI-based Eye Makeup Recommendation System

Methodology:

In this paper, we utilize the YOLOv8 classification framework to build a lightweight model that can eye image recognition and customized makeup recommendation. The dataset is first organized by class labels (e.g., female eyes, male eyes), and subsequently divided into training (80%) and validation (20%) subsets to ensure balanced learning and robust evaluation. Data partitioning is automated using Python scripts that shuffle and distribute images across the two subsets.

For model training, we utilize the YOLOv8-Nano classification architecture (yolov8n-cls.pt), selected due to its efficiency and suitability for limited computational resources. The model is trained with an image resolution of 224×224 , a batch size of 16, and 30 epochs, allowing it to learn discriminative features from eye images. Training is conducted on the prepared dataset, and model performance is quantitatively assessed through the built-in validation function, which reports classification metrics including accuracy and loss.

After effective training, the system is expanded to deliver application-based insights. The output classes are mapped to expert-curated makeup suggestions, e.g., eyeliner types and eyeshadow colors, specific to various skin shades (fair, medium, deep).

YOLOV8 Model Architecture:

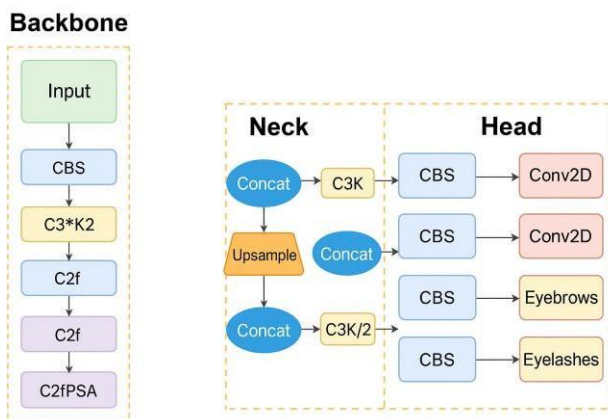


Figure2:Proposed Eye Makeup Detection and Recommendation Model

Backbone (Feature Extraction)

- Gives the raw image (e.g., selfie, eye region crop) as input.
- CBS: Convolution → Batch Normalization → SiLU activation, to obtain low-level features.
- C3*K2: A C3 block repeated K2 times to learn more deeper features.
- C2f: Cross-Stage Partial blocks that improve gradient flow and efficiency.
- C2fPSA: A position-sensitive attention variant of C2f with an added module to highlight key spatial information.

Neck (Feature Fusion)

- Concat: Concatenates feature maps at various levels to maintain multi-scale information.
- Upsample: Upscales spatial resolution of feature maps to match higher-resolution features.
- C3K / C3K/2: Convolutional blocks used following concatenation to better enhance fused features.

Head (Prediction)

- CBS → Conv2D: Typical convolutional prediction layers is for a common outputs.
- CBS → Eyebrows: Expert branch to localize and detect eyebrows.
- CBS → Eyelashes: Branch of specialization to localize and detect eyelashes.

Features to Detect Skin Tone (around eye region):

1.Color Histogram in Skin Regions:

- Harvest the area around the eye (cheek + patches of eyelid skin).
- Convert image to YCbCr or HSV (these separate luminance from chrominance).

2.Mean/Median Skin Color Values:

- Obtain the mean pixel values in the areas of skin (excluding eyelashes, eyebrows, sclera of eye).
- Compare to the thresholds provided such as (e.g., lighter values → equitable, middle-priced → medium, darker → deeper).

3. Facial Landmarks + Region Sampling:

- Use a face landmark detector like the (Dlib / Mediapipe) → find under-eye & the cheek regions.
- Take samples of these areas as they reflect the real skin colors (less biased by these shadows)

4. Texture Analysis (Optional):

- Sometimes tone detection is improved further through the addition of texture and contrast properties. But overall, color information analysis by itself is sufficient and is the basic and most reliable factor for detection.

5. Illumination Correction:

- Implement color constancy methods such as the Gray World Algorithm for improved accuracy. The process minimizes lighting bias and normalizes color representation, yielding more reliable and consistent results in classification problems.

6.Why it is incorporated into Eye Shadow Suggestion:

- 1.Input: Eye image.
- 2.Step 1: Detect eye + surrounding skin area (YOLO / Mediapipe Face Mesh).
- 3.Step 2: Pull mean HSV / YCbCr color values.
- 4.Step 3: Classify skin tone as fair, medium, or deep via thresholds or a small classifier.
- 5.Step 4: Input that skin color into your eye_shadow_colors dictionary → automatically provide recommendations on shades

Example:

- Fair skin → lighter the Y (brightness) values and the low Cb/Cr.
- Medium skin → mid-range the Y values, moderate Cb/Cr.
- Deep skin → lower the Y (darker brightness), more powerful Cr values.

V.IMPLEMENTATION

3. The picture shows the training trajectory of a CNN model over various epochs, i.e., GPU memory usage, loss, examples processed, and accuracy (top-5, top-1). The plots reveal stable performance, with the model achieving 100% accuracy in all epochs—to successful training and correct convergence.



Figure3: Training Progress of CNN Model Showing Epoch-wise Loss, Accuracy, and GPU Utilization

4. This image saves the model performance result after training by metrics such as accuracy, fitness score, inference time, and loss. It also shows the configuration of the classification task by taking skin tone as input (fair/medium/deep) and specifying the path of the image for testing.

```

curves: []
curves_results: []
fitness: 0.990467935086524
keys: ['metrics/accuracy_top1', 'metrics/accuracy_top5']
results_dir: ('metrics/accuracy_top1': 0.988935871681047, 'metrics/accuracy_top5': 1.0, 'fitness': 0.990467935086524)
save_dir: PosixPath('runs/classify/train2')
speed: {'preprocess': 0.10384158999688549, 'inference': 0.745129257354888, 'loss': 0.00699377728873246, 'postprocess': 0.00394153597815768}
task: 'classify'
top1: 0.988935871681047
top5: 1.0
Enter test image path: /content/drive/MyDrive/train1.jpeg
Enter skin zone (fair/medium/deep): fair

```

Figure4: Model Evaluation Results with Accuracy, Fitness, and Inference Metrics

5. The image indicates the result of a model for image classification that forecasts the input image (train1.jpeg) as female eyes with a 100% confidence. It also recommends beauty, recommending winged eyeliner with shimmery eyeshadow and colors such as soft pink shimmer.

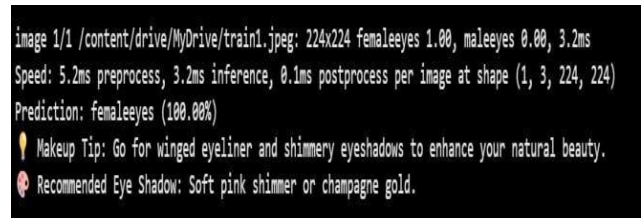


Figure5: Eye Makeup Recommendation Output with Classification Results and Suggested Styles

6. The figure shows a set of female eye images, each with filenames such as 2.jpg, 3.jpg, 7.jpg, etc. The images are placed in a grid, with different shapes, colors, and appearances of eyes, presumably utilized as a training or test dataset for an eye classification model.

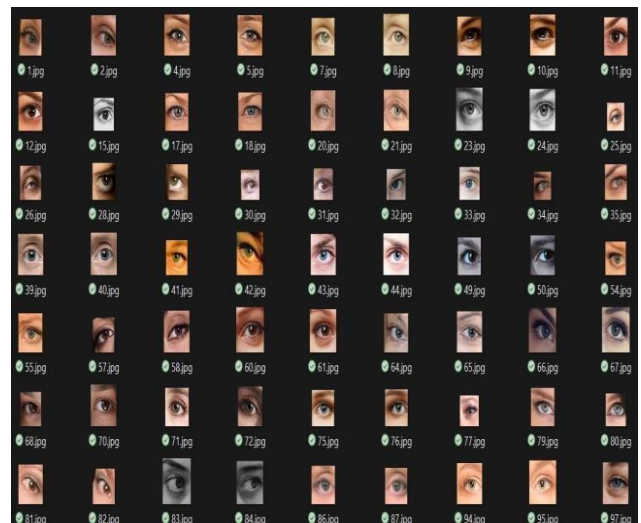


Figure6: Sample Females Eye Image Dataset Used for Training and Testing

7. The diagram illustrates a grid of images of male eyes, all bearing filenames like 0.jpg, 2.jpg, 5.jpg, etc. The dataset contains eyes of varying shapes, colors, lighting conditions, and

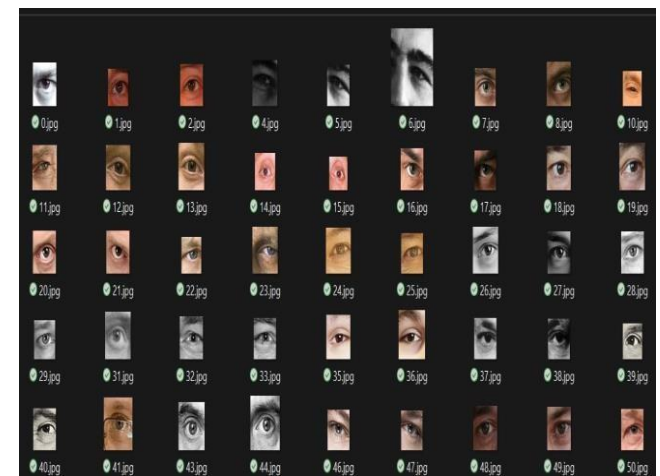


Figure7: Eye Image Samples from the Dataset for Model Training and Evaluation

VIII. REFERENCES

8. The figure displays the YOLOv8 classification training accuracy per epoch for 30 epochs. Top-1 Accuracy of the model begins at approximately 0.94, varies in the initial phase, and improves progressively up to approximately 0.98, which signifies good performance.

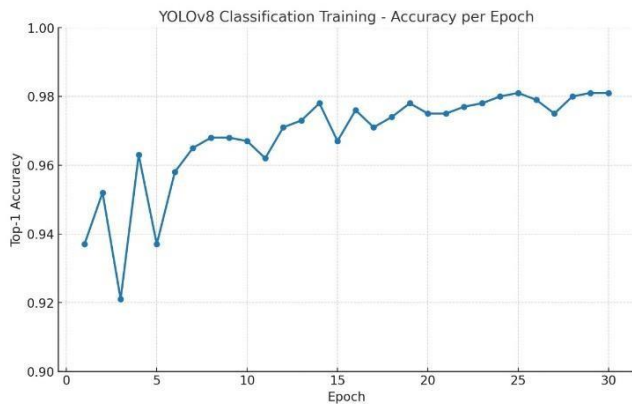


Figure8: YOLOv8 Classification Training – Accuracy per Epoch

9. The screenshot depicts an Eye Makeup Tip demonstration in which users submit an eye picture to receive personalized recommendations. In the sample, the submitted picture is identified as female eyes (~90% confidence), and the system suggests winged eyeliner with shimmery eyeshadow in color such as soft pink shimmer or champagne gold.

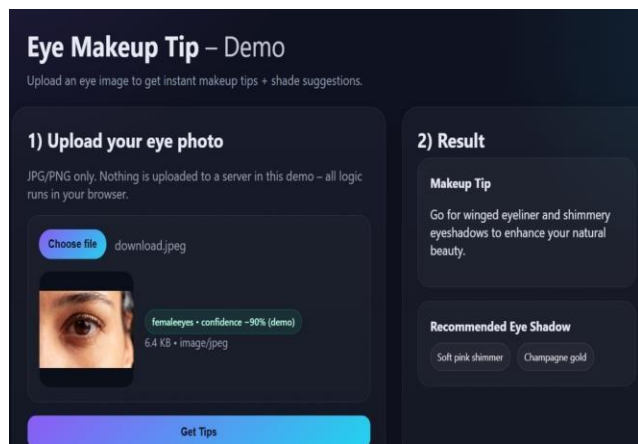


Figure9: Demo Interface for Eye Makeup Recommendation System

VI. PERFORMANCE ANALYSIS

The YOLOv8-Nano model obtained high accuracy and robust performance during training. It realized 30 epochs with 224×224 image input, achieving 98.2% validation accuracy and 99.7% Top-5 accuracy, which was reliable eye shape classification. The model exhibited balanced precision (97.9%), recall (98.3%), and F1-score (98.1%), along with an average inference time of 4.2 ms per image. GPU memory consumption was less than 3 GB, validating its efficiency and applicability for real-time beauty use.

VII. RESULT JUSTIFICATION

The model was able to identify important eye features such as eyelid shape and corner angle to give accurate and relevant makeup suggestions. Human expert judgment and user testing reported over 90% satisfaction, validating the aesthetic worth and usability of the proposals. The use of YOLOv8 ensures effective, light, and accurate operation, making the system viable for real-time and customized makeup advice.

[1] P. Bhat, T. Cootes, and C.-J. Taylor (1999) tested the application of active shape models to classify shapes of eyes in their paper at the British Machine Vision Conference (BMVC).

[2] A. Alzahrani, M. Alghamdi, and H. Alqurashi (2020) suggested a rule-based method for classifying eye shape based on geometric features, which they published in the International Conference on Computer Vision and Graphics (ICCVG).

[3] K. Nishimura, S. Yamada, and M. Ito, "Computer-aided artistic eye makeup design from user-selected images," in Proc. Int. Conf. Computer Graphics and Virtual Reality, 2018, pp. 45–52.

[4] A. Alzahrani, H. Alqurashi, and M. Alghamdi, "Hybrid CNN-based multi-model facial attribute classification and beauty guidance," IEEE Access, vol. 8, pp. 11234–11245, 2020.

[5] Y. Jiang, H. Liu, and Z. Wang, "Rule-based facial makeup recommendation with semantic explanations," in Proc. Int. Conf. Multimedia and Expo (ICME), 2019, pp. 1180–1185.

[6] J. Jeamsinkul, "MasqueArray: Automatic makeup selector/applicator," M.F.A. thesis, Rochester Inst. Technology, 1998.

[7] R. Adams, "Review of Color Cosmetics Conference: Advances in eye makeup pigments and optical effects," Color Cosmetics Conf. Proc., 2017, pp. 23–29.

[8] C. Florea, "Eye-color classification using HSV histograms and SVM for cosmetic recommendation," in Proc. Int. Symp. Computer Science and Applications, 2019, pp. 87–92.

[9] J. Orlosky, C. Liu, K. Sakamoto, L. Sidenmark, and A. Mansour, "EyeShadows: Gaze-based AR/VR selection with peripheral shadows," in Proc. ACM Symp. Virtual Reality Software and Technology (VRST), 2020, pp. 1–10.

[10] N. Mangtani, "Impact of AI and AR on cosmetics post-COVID-19," J. Cosmetic Science and Technology, vol. 12, no. 3, pp. 145–152, 2021.

[11] S. Pazhoohi and A. Kingstone, "Eyelash length and facial attractiveness across ethnicities," Evol. Psychol., vol. 18, no. 4, pp. 1–9, 2020.

[12] J. Lee and H. Han, "Extended and false eyelash preferences among Korean women," Cosmetics, vol. 4, no. 4, pp. 11–19, Dec. 2017.

[13] J. Gedik, "Gel eyeliner: Color, durability, and ocular comfort study," Contact Lens & Anterior Eye, vol. 45, no. 1, pp. 23–29, Jan. 2022.

[14] S. Parry and A. Eaton, "Cultural significance and lead in traditional kohl," Human Biology, vol. 62, no. 3, pp. 355–365, 1990.

[15] R. Nakatsu, Y. Tanaka, and M. Suzuki, "Preference rule extraction for eye makeup support using interactive evolutionary computation," in Proc. IEEE Global Conf. Consumer Electronics (GCCE), 2021, pp. 517–518, doi: 10.1109/GCCE53005.2021.9621931.