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AI Based Makeup Recommendation System: A Sustainable AI Solution for Women

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ABSTRACT

This paper describes the development of an AI-driven makeup recommendation application and how it was developed with the use of OpenCV and dlib to process the data on the back side and machine learning algorithms to execute a recommendation, and Flitter in order to operate the front-facing camera. The application gives unique recommendations to users depending on their face structure and their interests, to transform the way individuals shop makeup. The tool is more accessible to the art of cosmetics and utilizes AI to enable users to use it and enhance their natural beauty with confidence. It also uses sophisticated algorithms to detect facial characteristics like color of skin, shape of eyes, and color of lips to recommend appropriate cosmetic products and methods. This creative method is not only very simplifying to the make up process it also promotes creativity and self expression.

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1 Introduction

The beauty industry is not an exception because artificial intelligence (AI) and machine learning (ML) are changing the way of doing things in the industry. AI-powered applications in the cosmetics sector are becoming smarter and provide customized recommendations on makeup that nobody expected to happen. This study is aimed at developing an AI-powered beauty recommendation application that provides personalized makeup recommendations through a thorough study of the individual facial characteristics of any given user [1].

Conventionally, makeup consultations have relied on the experience of professionals and this is rather handy, but might also be subject to personal views.

The outcomes of these consultations may be different depending on the experience of the consultant, his/her biases, or even the fashion. In contrast, AI systems eliminate subjectivity by relying on complex machine learning algorithms that make recommendations more consistent, reliable, and equitable [2]. In the case of AI discussed in this paper, Flitter is the front-facing camera engagement tool on the AI platform, and the state-of-the-art machine learning (ML) and artificial intelligence (AI) tools reshape different industries, including the realm of the beauty industry. The cosmetics sector

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is one of the sectors where AI-driven applications are getting more advanced and offer ultra-personalized experience that would have been unthinkable before.

1.1 Motivation and Contribution of this Research

In this paper, I explain how an AI-driven makeup recommendation platform can be developed to provide individualized makeup recommendations by taking a critical analysis of a user facial features. Traditionally, the makeup consultations have relied on the opinions of the professionals, which are helpful, yet may be subject to the experience of the consultant, his/her personal opinions, or the latest trends. This may have various outcomes with regards to the person passing the advice. On the contrary, AI systems are less biased, with their recommendations being founded on data via high-order machine learning processes, which renders them more reliable and fair [2]. The core of this platform is computer vision technology that is critical in the accurate analysis of facial features such as the skin color, lips shape, eye features and cheekbones.

Through such details, the system can provide very personalized makeup recommendations that will assist in improving the natural appearances of a person [3]. There is also an improvement in the use of machine learning.

The beauty industry through making it more engaging, efficient and customized to its users [4]. The examples include OpenCV (assisting with the strong image recognition) and dlib (assisting with detailed facial landmarks identification) so that it is guaranteed that the images are analyzed and recommend making up in an accurate way [5], [6].

In the new apps, user satisfaction is largely influenced by personalization. With AI and big data, it is possible to provide a user with a highly personalized experience that corresponds to their preferences and characteristics [7]. This application utilizes such advancements and enables the user to test various make-up styles and receive personalized guidance depending on a specific analysis of the photo [8]. This not only assists users in making superior decisions but also they are able to experiment with new styles and trends.

Besides making the correct recommendations, AI enhances real-time experiences to users. The cameras on the front face of the user offer real-time visualization of the viewer to understand what the proposed makeup would appear like on the face of the user. This instant feedback allows users to view their make-up options and also customize it right away which makes the site more interactive and user-friendly [9]. The system is not fixed as well, but it evolves with the user interaction and ensures that it remains up to date with the current trends in beauty. The platform can be even enhanced with the use of deep learning models that would also give better and more relevant makeup suggestions in the future [10].

The beauty industry is becoming innovative due to the development of AI. AI-based beauty apps are very flexible and follow the preferences and tendencies of users in the market. This flexibility will guarantee that the users receive suggestions that will be compatible with their characteristics as well as fitting present beauty items and trends. Furthermore, the intelligent recommendation service of the platform tracks the changes in the industry by ensuring that the advice provided is current and aligned with the recent beauty advancements [2].

To sum up, this AI-enhanced makeup recommendation platform is the uninterrupted merging of technology and beauty. The software will make the selection and makeup application process easier by examining the features of a face and providing them with customized makeup suggestion. It encourages the use of creativity whereby users can experiment with different appearances without hesitation. As the AI keeps transforming the traditional beauty consultation, consumers can now decide more confidently and knowledgeably, therefore changing the manner in which makeup consultation is offered [2].

The key contribution of the given research is stated as follows:

A makeup suggestion platform using AI and presented in this paper is the logical step toward the flawless integration of technology and beauty. The site makes the process of selecting and applying makeup easier by analyzing and providing customized makeup tips based on facial features. This solution encourages creativeness where users are able to experiment with different looks comfortably. With the continued remodeling of the conventional aspects of beauty consultation by AI, the consumers are now able to make more confident and informed choices, which is changing the manner in which makeup advice is rendered.

2 Related Works

Artificial intelligence has been used more in the beauty industry, particularly in systems which imply make-up to suit people. Numerous AI-based applications leverage machine learning by providing customized beauty recommendations. To illustrate, Luo and Li examined the adoption of AI in the beauty industry and demonstrated how the industry has evolved to a stage where the companies no longer apply the old techniques but the new ones, which rely on data to provide individualized advice. Zhang and others developed a makeup recommendation system based on convolutional neural networks and it demonstrates how AI can scan the faces of individuals and recommend makeup that best fits them. In line with this, Liang and others emphasized that personalized recommendations are important in beauty apps as they significantly enhance the user experience.

One of the most important elements of such applications is the ability to detect facial features, since the accurate recognition of such elements as the eyes, lips, and the tone of the skin will enable hinting at the appropriate makeup.

Kazemi and Sullivan came up with a facial match technology that is extremely fast which is currently prevalent in real-time make-up applications. Another basic tool used to work with images, Bradski OpenCV library has also contributed to facial feature analysis enhancement in makeup recommendation systems. Jiang and colleagues considered applying deep generative networks to do make-up transfer, which allows users to preview their new make-up and apply it to their faces[11].

Dlib is a machine learning tool that is used to achieve high accuracy on face analysis tasks and which can detect facial landmarks. In reference to facial recognition, which is relevant to makeup recommendation systems, King talked about the application of Dlib in making such recommendations. The application of Flitter technology on the operation of front-facing cameras, as discussed by Zhang and their team, enables effective interaction of feedback (real-time). This enables an app to be more interactive and user-friendly.

Overall, such advances in artificial intelligence, machine learning, and image recognition have contributed immensely to the makeup recommendation systems giving out more personalized, correct, and easier to use experiences.

The purpose of this research is to simplify the process of makeup through the use of these technologies and make it more personalized because it will be easier and pleasant to use.

A. Research Gap Analysis

An essential part of AI-powered makeup recommendation systems is personal color analysis. The idea is to determine the user's undertone—whether neutral, cold, or warm—and complement it with appropriate cosmetics. In their study of AI's usage in personal color analysis, Luo and Li [1] focused on deep learning's function in classifying users according to their skin tone, hair color, and eye color. In a similar vein, Zheng et al. [10] emphasized the significance of precise color identification for customized beauty experiences by concentrating on skin tone analysis using machine learning approaches. This approach ensures that makeup recommendations enhance natural features by selecting shades that complement the user's personal color palette.

Deep learning models such as CNNs and GANs (Generative Adversarial Networks) are used to perform automated personal color analysis. GANs have shown particular success in virtual try-on technologies, where users can visualize how different makeup shades look on their unique skin tones [12]. The virtual makeup systems allow users to experiment with various beauty products and techniques without commitment, promoting creativity and self-expression. By integrating virtual makeup functionalities into AI-based recommendation systems, applications like the one presented in this research provide a comprehensive beauty experience that merges product selection with user-friendly virtual try-on options.

ML is required to discover patterns among the user data and develop individualized makeup suggestions. A prior work by Zhang et al. [3] employed CNNs to learn features of face makeup and demonstrated how ML systems can drive a higher accuracy in the recommendations. In a similar vein, Hartley

B. Personal Color

One of the most important elements of AI- powered makeup recommendation is personal color analysis. The idea is again to determine the undertone of the user, be it warm, cool, or neutral, and correlate it with appropriate makeup products. Luo and Li [1] reviewed the application of AI to personal color analysis, and the authors focused on deep learning as the division of users according to skin tone, hair color, and eye color. On the same note, Zheng et al. [12] concentrated on skin tone analysis with machine learning algorithms and emphasized the value of correct color detection of personalized beauty. This method makes sure that makeup suggestions will augment various natural characteristics by selecting tones that will match the personal color palette of the user.

CNNs and GANs are deep learning models to perform automated personal color analysis. GANs have demonstrated success specifically in technology of virtual try-on, enabling users to see how various makeup shades appear on their own skin colors [7]. Using these technologies, makeup recommendation systems will have access to more customized recommendations that will comply with personal aesthetics as presented by Krizhevsky et al. [5].

C. Virtual Makeup

Virtual makeup apps have become popular in recent years and will enable users to experiment with makeup styles without having to apply products physically. Jiang et al. [10] investigated virtual transfer of makeup through deep generative networks, which allow people to apply various appearances in real-time. This would give users an instant visual representation of how the makeup products such as foundation, eyeshadow and lipsticks would look on their face hence simplifying the process of deciding which to buy as far as makeup is concerned. Virtual makeup [13] applications have also heavily used the openCV-based tools to give the effect of a makeup on facial features with the use of efficient image processing tools.

Additional research by Shi et al. [14] has used GANs to generate very realistic virtual makeup appearances that increase the interactivity and engagement of the user. By using these virtual makeup systems, one can use different types of beauty products and techniques without making a commitment, which encourages people to be creative and express themselves. Applications such as the one proposed in this study offer a unified beauty experience by combining product choice with the virtual try-on feature by integrating virtual makeup features into the recommendation system through AI.

D. Machine Learning in Makeup Recommendation Systems

Machine learning (ML) is essential to detect trends in the data of users and provide them with personalized makeup suggestions. The research carried out by Zhang et al. [3] used CNNs to extract features used in facial makeup, which shows that in the case of ML algorithms, the accuracy of recommendations can be enhanced. Similarly, Hartley and Zisserman J. [5] discussed the way ML can be used to scale beauty platforms by automating feature recognition. These systems examine user behavior and it is possible to dynamically vary product suggestions in accordance with individual tastes.

E. Makeup Transfer Techniques

Another important area is make-up transfer, which is an option that enables the users to see the appearance of a makeup and apply it physically. Wang et al. [6] created a system based on deep generative networks which were effective in transferring makeup styles to a different image. This transfer attribute makes it possible to make personalized suggestions, which enhances user engagement. Shi et al. The works of [14] went further and employed generative adversarial networks (GANs) to generate naturalistic and customizable virtual makeup appearance.

F. Real-Time Makeup Applications

Make-up systems that are real-time take advantage of AI to provide feedback to the user in real-time. The real-time positioning of various makeup products on the face of a user is possible by integrating Flitter to enable front-facing camera interaction, as proposed by Zhang et al.

[15]. It is the immediate feedback that helps to improve the user experience, as it gives correct and timely suggestions regarding the face images found by the ML algorithms [6].

3 Proposed Method

The cosmetics recommendation system is an AI-based algorithm that is de- signed to offer users personalized makeup recommendations based on their facial features (skin tone, face shape, and other unique landmarks) including eyes, lips, and cheeks, among other features. The technology uses image processing with machine learning algorithms to identify facial features and use make-up digitally. It involves taking a photo either by using the front-facing camera or uploading a photo that already has been taken. Once the picture has been uploaded, the dlib package is applied to find out the landmarks of the face, ensuring that it is accurate in defining the features such as the lips, eyes and cheeks. The next process is a segmentation where the parts of the face are isolated so that the virtual cosmetics can be applied.

Then the system performs a real-time analysis of facial features and makes a suggestion according to the characteristics found by it. As an example, the skin tone analysis can be applied to suggest a shade of foundation, whereas likes and dislikes of the user and the shape of the face are applied to the selections of lip, and blush colors. A more life-like appearance is accomplished through the application of the Gaussian blurring effects of which it ensures the blush and foundation blends naturally.

Convolutional neural networks (CNN) are incorporated into the beauty recommendation model to increase the precision of makeup application and face feature recognition. To identify various facial shapes and cosmetic styles, the model is trained using a sizable collection of makeup photos. The suggested approach uses cutting-edge machine learning algorithms to offer customized makeup recommendations. The technique mostly combines landmark extraction and personal color analysis to identify and analyze important facial features. The system's primary components are delineated in the ensuing parts, as illustrated in Fig. 1.

3.1 Facial Landmark Extraction

We initially extract the face landmarks in order to apply virtual cosmetics based on the individual's colour. We used the dlib to accomplish it. Dlib is a C++ implementation of a machine learning algorithm. It can be used on a number of systems and is an open library. The dlib has a pretrained face marker that lets you extract 68 coordinates that correspond to the face structure. An example of 68 landmark coordinates that dlib was able to extract is displayed in Fig. 2. We refer to the multiple uses of the retrieved facial landmarks as DFL (Dlib Facial Landmark).

The technique identified the main face landmarks, paying particular attention to the lips, eyes, eyelens, and blush regions. Makeup applications such as blush, lipstick, and eyeliner are linked to each milestone. The coordinates for the cheeks, lips, and eye corners are described in Table 1 along with their significance for applying cosmetics.

3.2 Personal Color Analysis

Finding the right cosmetic tones depending on skin tone and other face features requires personal color analysis. Using the landmarks identified in the preceding section, masks are created for particular facial regions, such as the skin and blush areas. This guarantees that the analysis for color selection is limited to the cheek area.

3.2.1 Extraction of Iris Color

We first identify potential eye locations where the iris may reside in order to detect it. There are twelve coordinates in total for each eye region that was retrieved using the dlib. Since the human eye is typically elliptical in shape, we can distinguish between two distinct curves: the upper curve and the lower curve. To obtain two curves accurately, we applied 1D interpolation (1-dimension interpolation) to the upper curve and the lower curve. The correct eye region can be extracted through these two curves, as shown in Fig. 3.

3.3 Virtual Makeup

This section explains the techniques for applying makeup digitally. The system applies effects using the appropriate algorithms after employing landmark extraction to identify the best facial area for each type of makeup. For instance, foundation is applied to the

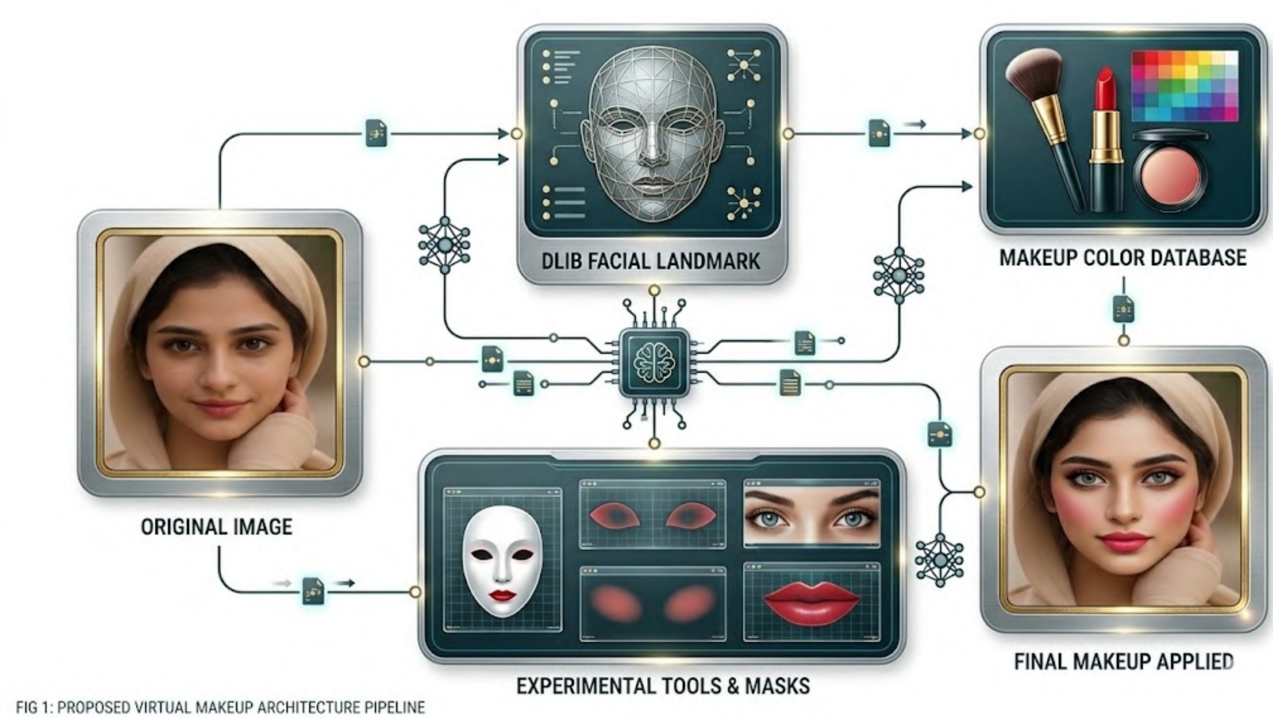

Figure 1. Methodology diagram.

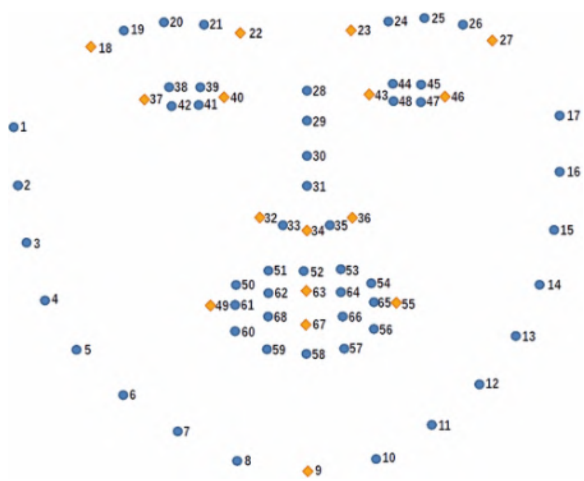

Figure 2. 68 points from dlib's facial landmarks

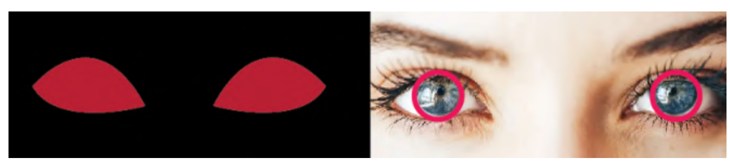

Figure 3. Example of pupil detection using dlib

skin using a masking technique, and blush is applied to the cheeks using Gaussian blurring to give a realistic gradient look. Applying eye lens entails determining the iris region and simulating various contact lens colors using curve fitting interpolation. The makeup type, detected region, algorithm used, and effect applied are summarized in Table 2.

To apply the makeup base, we need to know the skin region of the whole face [6]. The skin detection rule can be expressed as:

$$\begin{aligned} &R > 95 \wedge G > 20 \wedge B > 20 \wedge \\ &\big(\max(R, G, B) - \min(R, G, B)\big) > 15 \wedge \\ &|R - G| > 15 \wedge R > G \wedge R > B. \end{aligned} \tag{1}$$

However, even if this condition is satisfied, the hair color, background, clothes, and the like could be similar to the color of the skin, and they may be recognized as a skin region in some cases. To solve this problem, we limit the facial skin region as follows. Fig. 4 shows an example of the extracted face region. The white area is the region where makeup foundation should be made.

After setting four points, we generate closed curves

Table 1. Facial Landmark Points and Their Uses

Facial Landmark	Coordinates (x, y)	Description	Makeup Application
Eye Inner Corner (L/R)	(x_1, y_1)	Marks the inner corner of the eye.	Eyeliner, eyeshadow, eye lens
Eye Outer Corner (L/R)	(x_2, y_2)	Marks the outer corner of the eye.	Eyeliner extension, eye lens
Lip Corner (L/R)	(x_3, y_3)	Defines the corners of the lips.	Lipstick boundary detection
Cheek Bone (L/R)	(x_4, y_4)	Key point for cheekbone position.	Blush application

Table 2. Virtual Makeup Application Techniques

Makeup Type	Region Detected	Algorithm Used	Effect Applied
Foundation	Full face (Skin)	dlib landmark + masking	Smooth base tone
Blush	Cheeks	Gaussian blurring	Natural gradient effect
Lipstick	Lips	1D interpolation	Lip color and texture change
Eye lens	Eyes (Iris)	Curve fitting interpolation	Contact lens simulation

through applying 1D interpolation to these four points. Then, we extract all the coordinates inside the closed curves. In the case of blush, since it is expressed in both cheeks, the coordinates of the final cheek region are extracted by symmetrically aligning the cheek region coordinates extracted from the right cheek with reference to the center of the face, as shown in Fig. 5.

The lips region, which can be obtained by DFL, is divided into oral angle, upper lip, and lower lip as described in Fig. 6(a). To extract exact lips line, we apply 1D interpolation to each segmented region. Connecting all points forms lips shape which is shown in Fig. 6(b).

Personal color analysis enhances the precision of makeup recommendations by ensuring that the suggested products harmonize with the user's natural complexion. The color analysis module relies on advanced algorithms for color detection and classification, which has been previously explored in [16–19].

3.4 Data Collection

The data collection is an important module in any machine learning project and quality and relevancy of the data is vital to the performance of a system. In this project, we gathered a large amount of data that was carefully preprocessed to suit the requirements of our AI-driven recommendation system of makeup.The suppression of the data filtering is mainly on lipstick, eye lens, and blush. The next sections describe the sources of the data, the structure, preprocessing methods and filtering.

3.4.1 Data Sources

: Data to be used in this project were obtained through a variety of publicly available beauty and cosmetics databases, along with hand collected data of user submissions. The main sources were images provided by the users as well as annotated with the facial features and makeup properties like the type of lipsticks, the type of blush, and the type of eye lenses. Every product was marked with metadata such as product data, user reviews and makeup style preferences.

3.4.2 Dataset Structure (Prior to Filtering)

The original dataset was made of an incredibly diverse array of features which were not directly pertinent to the overall aims of this work. These features were founda-

Figure 4. Mask of skin area

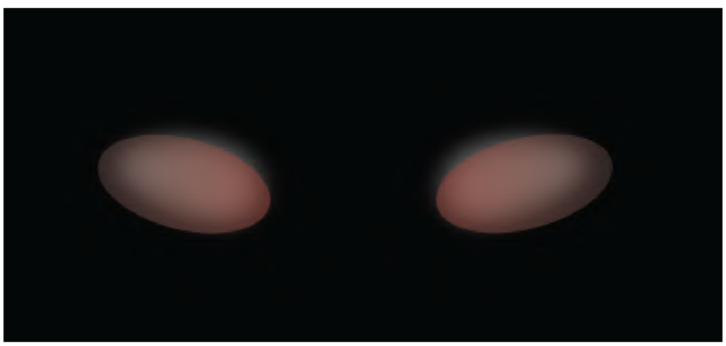

Figure 5. Mask of blush area

tion color, eyebrow shape, and types of eyeshadows as well as such attributes as light conditions, skin blemishes, and makeup brands, as shown in Table 3.

3.4.3 Data Preprocessing

Before applying the filtering, several preprocessing steps were conducted to ensure the data quality. These steps included cleaning the dataset by removing incomplete entries, handling missing values, and standardizing data formats. Furthermore, image data were resized, normalized, and converted to consistent formats to ensure smooth processing by the AI system. The preprocessing stage also involved the transformation of raw images into analyzable features using image processing techniques such as edge detection and color analysis. Before filtering, various preprocessing mechanisms are

Figure 6. Example of lips region detection

done to guarantee data quality. The process involved cleaning up the data, the incomplete data, and dealing with the missing data and standardizing data. Moreover, the images data were rescaled, normalized and changed to similar formats to make the data easy to be processed by the AI system [20–22]. The preprocessing phase was also related to conversion of the raw images into features that can be analyzed by image processing methods like color analysis and edge detection.

3.4.4 Filtering Process

In a bid to make the dataset more specific to the requirement of our AI makeup recommendation system, we used a filtering process to remove irrelevant features. This was aimed at targeting the features that are closely related to lipstick, eye lens and blush. We filtered the data we subsystematically removed data referring to foundation, eyeshadow and lighting conditions and to anything that is not connected to the face itself, to optimize the work of the system.

3.4.5 Final Dataset (After Filtering)

The data underwent the filtering process, and it has been narrowed down to three main features; lip- stick, eye lens, and blush. The latter data is more pertinent and cleansed [23–26].The structure of the filtered dataset is presented in Table 4.

3.4.6 Data Availability

The dataset applied in the current study consists of the raw, original one, and the final, processed one with the emphasis on lipstick, eye lens, and blush. The dataset is availed in csv format and is available at the following link:*Complete dataset before and after filtering*.

4 Experimental Results

The suggested AI-based makeup recommendation system was tested on the basis of its precision, end-user

Table 3. Dataset structure before filtering

lips_g	lips_b	eyes_r	eyes_g	eyes_b	lipstick_r	lipstick_g	lipstick_b	eyeshado	eyeshado	eyeshado	eyeshado	eyeshado	eyeshado	eyeshado	eyeshado	eyeshadow2_b
91	121	74	87	106	163	105	103	88	56	54	128	89	81	175	142	124
94	82	51	41	41	184	123	112	85	61	58	113	84	75	176	131	104
122	128	97	92	86	177	81	98	111	73	64	153	107	89	203	168	148
118	103	46	36	33	183	122	107	116	58	48	142	86	66	165	115	88
79	86	55	38	41	45	41	55	102	63	53	174	129	103	219	173	155
96	93	96	79	66	156	79	79	89	53	53	127	78	72	167	109	92
90	84	23	19	20	143	96	93	79	58	51	119	88	78	174	135	118
94	100	82	72	66	161	100	102	108	82	72	130	100	89	153	118	100
104	99	79	62	58	185	95	94	82	56	52	115	79	69	140	95	78
113	133	62	45	52	198	101	131	81	40	49	136	70	73	195	120	124
107	116	88	61	60	213	120	118	70	59	78	115	88	97	165	124	125
106	119	86	73	70	101	36	54	70	45	48	114	83	81	151	114	108
128	133	84	93	96	136	30	44	67	65	66	134	126	121	180	172	160
129	131	101	76	66	221	136	134	93	69	66	143	110	103	191	149	134
116	106	87	74	58	186	100	87	67	31	13	128	71	34	196	138	100
109	116	92	59	56	191	107	114	122	87	90	169	120	119	170	150	117
68	77	81	57	54	122	48	75	108	62	63	141	91	113	164	121	110
88	92	60	56	52	161	87	93	88	60	55	122	87	78	148	107	92
116	117	105	91	93	201	121	127	114	77	70	160	112	99	229	183	170

Table 4. Dataset structure after filtering

id	blush_r	blush_g	blush_b	lens_r	lens_g	lens_b	lipstick_r	lipstick_g	lipstick_b
Oqp-lhgDi	148	91	121	74	87	106	163	105	103
_DpQTFNF	154	94	82	51	41	41	184	123	112
Ih5VYM_E	181	122	128	97	92	86	177	81	98
MB38nvK_	179	118	103	46	36	33	183	122	107
heQXH5nv	162	79	86	55	38	41	45	41	55
DNW5GnS	174	96	93	96	79	66	156	79	79
gnBAL1-w	131	90	84	23	19	20	143	96	93
ew6XNp1	163	94	100	82	72	66	161	100	102
9CKcZtPLu	181	104	99	79	62	58	185	95	94
36CXZWgs	199	113	133	62	45	52	198	101	131
DLH7MCU	203	107	116	88	61	60	213	120	118
pxrYXUYLc	177	106	119	86	73	70	101	36	54
XNOa_xJL	173	128	133	84	93	96	136	30	44
2vV2V-jhl	198	129	131	101	76	66	221	136	134
7MC0hGCi	221	116	106	87	74	58	186	100	87
HAd1uNdc	199	109	116	92	59	56	191	107	114
AngNAkLV	122	68	77	81	57	54	122	48	75
3q-mX6BY	135	88	92	60	57	52	161	87	93
DL13Bffka	191	116	117	105	91	93	201	121	127

satisfaction, and system efficiency with regard to various makeup products. The exper- mental findings are segmented into different subgroups bringing into consideration foundation, blush, lipstick, and eye lens. The analysis of each product was done in terms of processing time, accuracy, and user feedback.

4.1 Graph Analysis and Model Comparison

4.1.1 Comparison of Accuracy of Makeup Features:

This paper gives a comparative study of the three models, dlib landmarks, CNN and facial landmark model, on three makeup features, that is, eye lens, lips and blush.

Eye Lens: CNN has the most accuracy at 90% and this shows that it is better in detecting and analyzing this feature. Dlib landmarks take the second place at 85% and the facial landmark model comes in at 82%. As shown in figure 7. This means that CNN is resilient on fine-grained detection processes.

Lips: CNN is the most real at 88%, followed by dlib landmarks at 85% and lastly the facial landmark model with 80% as shown in (Fig. 7). Such a stable performance of CNN points out to its sophisticated image feature recognition features.

Blush: CNN accuracy is reduced to 85%, and dlib landmarks and facial landmark model are 78% and 77%, re-

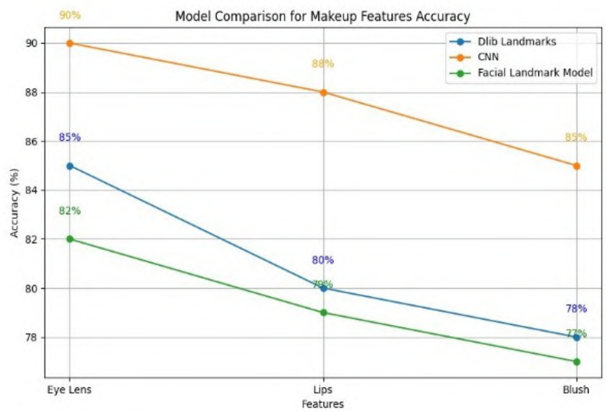

Figure 7. comparison for makeup feature accuracy

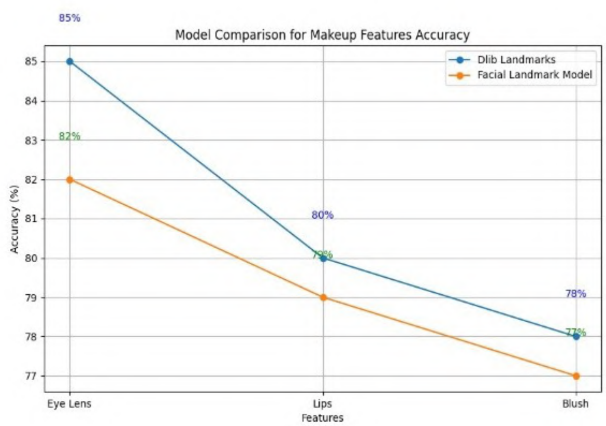

Figure 8. Accuracy comparison (dlib vs facial landmark model)

spectively (Fig. 7). The fact that CNN is the market leader, however, implies that it cannot accurately capture the broader parts of the face such as the blush application.

Significant Observation: CNN is the most successful in identifying detailed facial features compared to the other two models, and it is more accurate with all the features. Dlib landmarks are competent and the facial landmark model can be improved.

4.1.2 Comparison of Accuracy (dlib vs. Facial Landmark Model)

This graph as shown in Fig. 8 will be a more specific comparison of dlib landmarks and the facial landmark model on the same features of makeup.

This graph (Fig. 8) provides a focused comparison

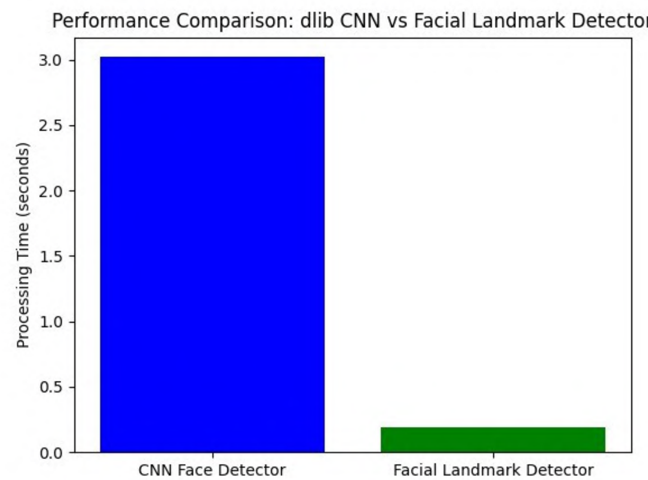

Figure 9. Processing time comparison between CNN and facial landmark detector

between dlib landmarks and the facial landmark model across the same makeup features.

- **Eye Lens:** dlib achieves 85%, outperforming the facial landmark model at 82%.
- **Lips:** dlib maintains higher accuracy at 80%, while the facial landmark model drops to 79%.
- **Blush:** dlib scores 78%, whereas the facial landmark model lags slightly behind at 77%.
- **Key Insight:** dlib is always better than the facial land- mark model, and thus it is a more viable choice in case one wants computa- tional efficiency and fair accuracy.

4.1.3 Processing Time Comparison

This graph (Fig. 9) assesses the processing time of the models which is the comparison of CNN face detector and facial landmark detector.

- **CNN Face Detector:** The processing time is significantly higher, approximately 3 seconds, reflecting the computational complexity and resource demands of CNN-based models.
- **Facial Landmark Detector:** This model processes data in under 0.5 seconds, showcasing its efficiency and suitability for real-time applications, albeit with lower accuracy.

Figure 10. Lip region detection and lipstick application

- **Key Insight:** While CNN provides higher accuracy, it is computationally expensive. In contrast, the facial landmark detector offers faster results but compromises on precision. This trade-off is critical in determining the application's performance balance between accuracy and speed.
- **Conclusion of the Section:** The analysis highlights a trade-off between accuracy and processing time.
- **The Use of CNN:** Best suited for applications requiring high accuracy in feature detection but may face limitations in real-time use due to its longer processing time.

4.1.4 Examples of Makeup Application Results

As shown in figures 10,11,12.

4.1.5 Conclusion of Model Comparison

The analysis highlights a trade-off between accuracy and processing time.

- **CNN:** Best suited for applications requiring high accuracy in feature detection but may face limitations in real-time use due to its longer processing time.

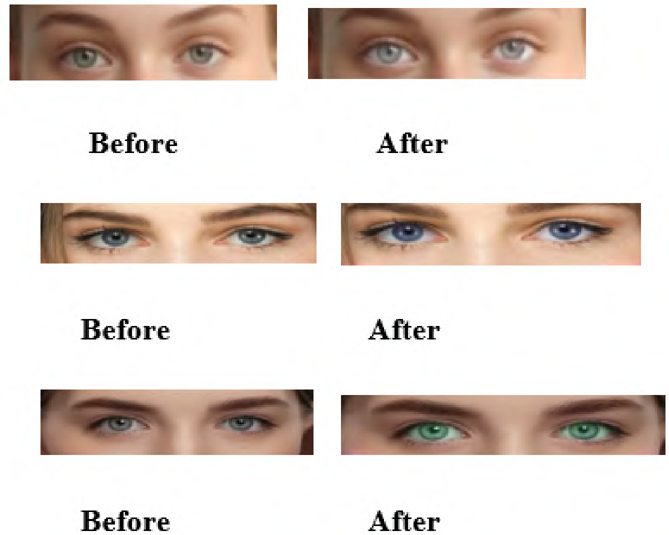

Figure 11. Iris detection and eye lens application

- **dlib Landmarks:** Balances accuracy and speed, making it an optimal choice for moderate-accuracy requirements with faster response needs.
- **Facial Landmark Model:** Ideal for real-time applications with minimal processing power but may require enhancements for higher precision.

The choice of the model in the AI makeup suggestion application depends on the specific priorities of the system, such as accuracy, speed, and resource availability.

4.2 Block Diagram

The AI makeup suggestion application block diagram (Fig. 13) outlines two main interfaces, namely: the user interface (UI) and the administrator interface. On the user interface, the user is taken through a smooth experience which begins with posting their photos, getting personalized makeup recommendations and also trying different styles. The interactive process is supported by advanced image analysis based on the analysis of skin tone and face shape to give personalized make-up suggestions based on AI algorithms and a powerful database of products.

The admin interface on the other hand provides the administrators with valuable tools that are required in managing and enhancing the system. They are able to change the algorithms which operate the makeup sug-

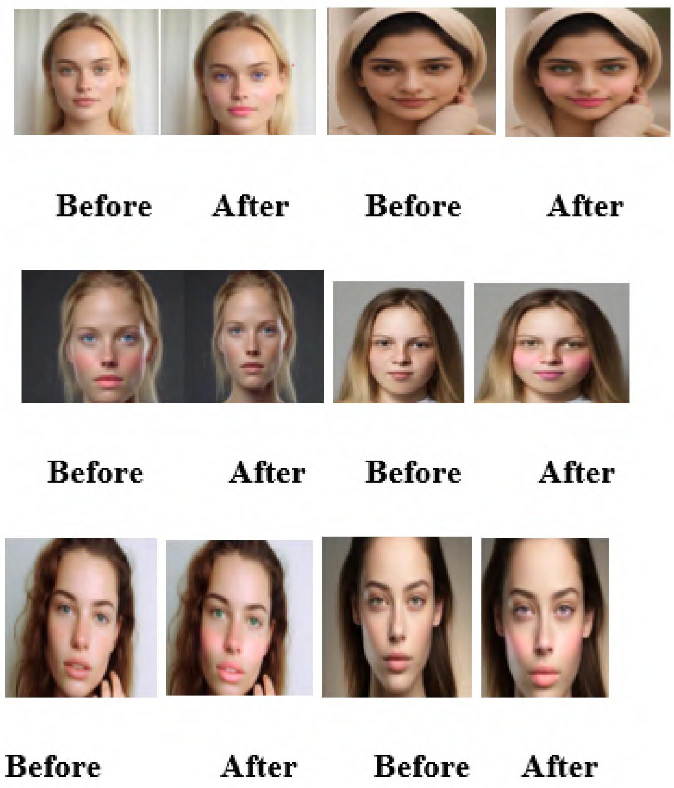

Figure 12. Overall face makeup application

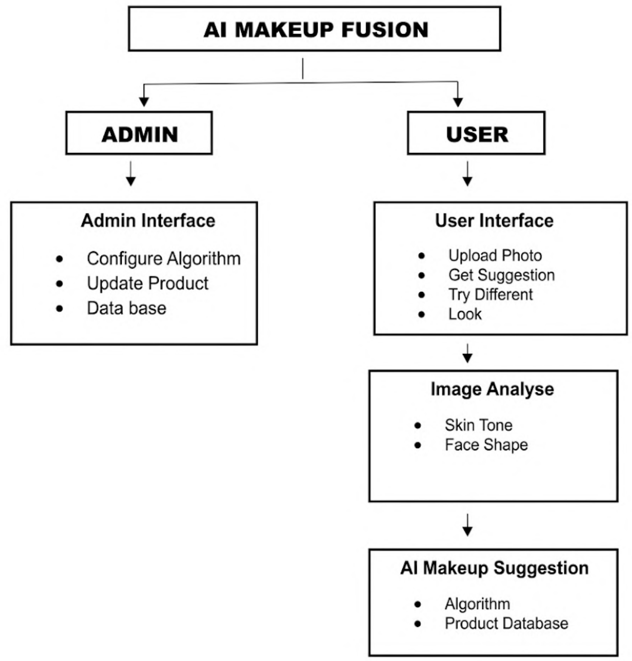

Figure 13. Block diagram

gestion engine, ensuring that it remains current with new trends in beauty and user preferences. The interface will also be easy to update the product database hence users will always get access to the latest makeup products and styles. Such an arrangement will provide users with an excellent experience and admins with the opportunity to maintain the system of recommendations working efficiently.

4.3 Flow Chart

The algorithm of the AI makeup suggestion applica-tion starts with a user authentication point, whereby users either pass through a registration process step, or log in when they are already registered. After a successful authenticate, a user is asked to take a picture to undergo the detailed analysis and the elements of the skin tones and the facial lines can be highlighted (Fig. 14). It is based on this information that the intelligent makeup recommendation system of the application is created and suggests personalized recommendations corresponding to the preferences of users.

After the phase of makeup suggestion the user will be involved in an interactive feedback loop where they will analyze the proposed appearance against their expectations. In case the users indicate that they are satisfied with the suggestions, then the process will end smoothly. In some situations, however, when users want to get more refined or other alternative suggestions, the application repeats itself, offering more options of makeup until the user is satisfied. This refinement process is akin to the optimization principles of user- centric design and reflects the desire of the app, which is to provide unique and high-quality makeup recommendations in accordance with personal tastes and preferences.

4.4 Use Case

The use case diagram (Fig. 15) of the AI make-up suggestion application illustrates the core features that can be used by the users and administrators. Users are allowed to post photos, receive makeup suggestions, test different fashions, log in to receive personal services, create

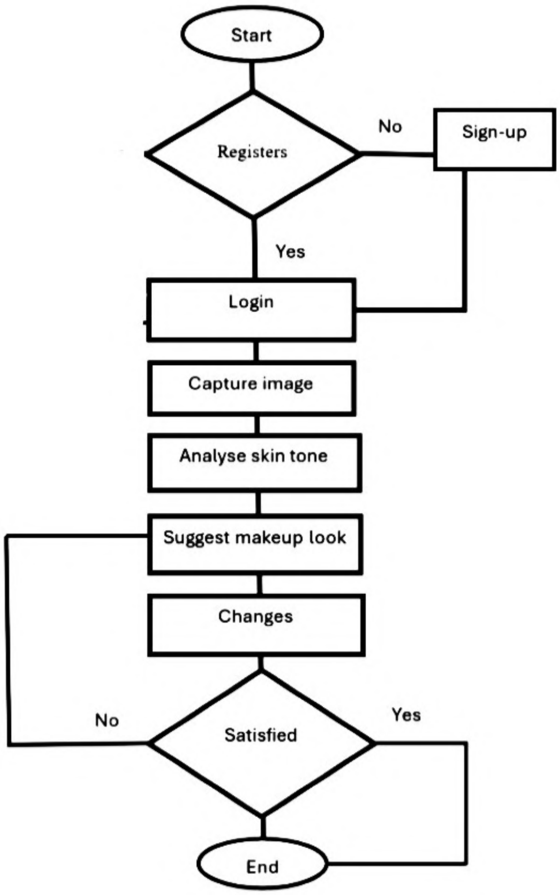

Figure 14. Flow chart diagram

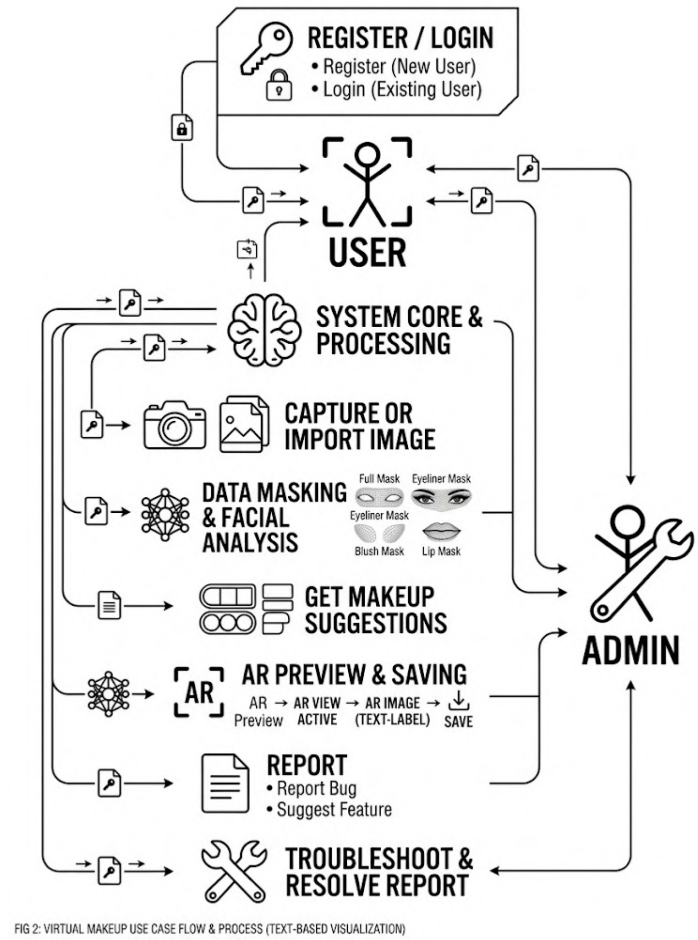

Figure 15. Use case diagram

new accounts, and report issues they encounter using the application. This comprehensive use case diagram outlines the core interactions and functionalities within the AI makeup suggestion application, ensuring a seamless and user-centric experience while providing administrators with the tools needed for effective system management and optimization.

Such features as the creation of algorithms to provide more appropriate make-up recommendations, maintaining the product list in line with new trends and products, correcting those issues reported by users make the system smoother and easier to operate, and maintaining user accounts. This use case diagram illustrates the key functionality of the AI makeup suggestion app to ensure that the user experience of the system is both engaging and user-centered and provides the admins with the tools necessary to manage the system and make it better.

5 Conclusion

The creation of the AI-powered app that provides recommendations to users on what to apply to their face proves that the beauty industry can be transformed by the use of cutting-edge machine learning methods, the ability to detect facial landmarks, and the preference to analyze and predict the colors that suit the customer best. The application offers personalized make-up recommendations depending on the facial characteristics of each individual such as the tone of the skin, the shape of the eyes and the lips with the help of OpenCV and Dlib. With the addition of real time camera interaction Flitter has provided a perfect and interactional experience that makes it easier to use and more accessible. This new technology will encourage self-expression and confidence with customized suggestions and streamline the makeup selection process. The app also enables people to test various styles of make-up in a virtual world, which can aid in minimizing waste of products, and also help them to discover products that can more accurately fit their specifications. The subsequent enhancements could be aimed at increasing real-time performance, introducing a more detailed analysis of skin, and increasing the functionality of the app. This project is a significant breakthrough regarding the application of AI in the daily life of people, particularly in fashion and beauty.

Authors Contributions

Mohammad Asad Abbasi: Conceptualization, Methodology. **Abdullah Ayub Khan:** Software implementation, Data curation, Writing-Original draft preparation. **Kashif Laeeq:** Software Validation. Shakir Karim Buksh: Writing. **Muhammad Ovais Akhter:** Reviewing. **Aurangzeb Rashid Masud:** Editing.

CONFLICT OF INTEREST

The author of this paper declares that there is no conflict among them.

Data Availability Statement:

The dataset used in this study is not publicly available due to ethical, privacy, and institutional restrictions involving sensitive dermatological and subject-related information. However, the dataset may be made available from the corresponding author upon reasonable request, subject to approval by the relevant institutional ethical review committee and compliance with data protection regulations.

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Not applicable.

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