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Cosmetic Product Suggestion System Based on Facial Features and Skin Features

[1]Shenal Perera, [2]Sulakshana Ranaweera, [3]Ravindu Induwara, [4]Rasindu Indusara, [5]Geethanjali Wimalaratne, [6]Sathira Hattiarachchi

[1,2,3,4,5,6]Department of Information Technology, Sri Lanka Institute of Information Technology, Malabe, SriLanka

Authors E-mail: [1]it20228262@my.sliit.lk, [2]it20247690@my.sliit.lk, [3]it20164676@my.sliit.lk, [4]it20242640@my.sliit.lk, [5]geethanjali.w@sliit.lk, [6]sathira.h@sliit.lk

***Abstract* - The cosmetic product suggestion system based on facial, skin, hair and scalp features areproposed solution to help individuals find suitable cosmetic products for their unique skin and facial features. The proposed system employs a fusion of machine learning algorithms and advanced image processing techniques for the comprehensive analysis of facial images, enabling the precise identification of distinctive skin attributes such as skin type, texture, tone, and blemishes. Based on the identified features, the system recommends cosmetic products that are best suited for the user's skin type and facial features. The suggested products include skincare products such as cleansers, toners, moisturizers, and treatments. Overall, the cosmetic product suggestion system based on facial features and skin features has the potential to help individuals make informed decisions about the cosmetic products they use, leading to improved skin health and appearance. The efficacy of the devised model is assessed across diverse metrics, including accuracy, precision, and recall. Findings demonstrate the proposed model's adeptness in accurately discerning gender and skin conditions. This model has the potential to be used in various applications such as medical diagnosis, cosmetics, and personalized skincare recommendations.**

Keywords: Product Recommendation, Demographics Identification, Facial Skin Conditions Detection, Skin Diseases detection, Hair and scalp Condition Detection.

I. INTRODUCTION

In today's dynamic beauty landscape, cosmetics and skincare products have transcended mere aesthetics to become essential tools for self-expression and self-care. These products cater to diverse individual needs, addressing skin concerns, enhancing natural features, and bolstering self-confidence. The array of options available reflects a deeper understanding of varied skin types, tones, and textures, accommodating inclusivity and embracing individuality. As a result, cosmetics and skincare products hold immense value, empowering individuals to curate personalized routines that resonate with their uniqueness. In the rapidly evolving cosmetics industry, the demand for personalized solutions tailored to individual skin types, hair textures, and facial features has surged. Addressing this need, this research paper discusses cosmetic product recommendation system driven by machine learning and computer vision. By analyzing facial and skin attributes through advanced algorithms and image processing, the system discerns characteristics like skin tone, texture, and imperfections, culminating in intelligent recommendations spanning makeup and skincare products. Anchored in extensive datasets encompassing facial images, intricate skin details, and a comprehensive cosmetics database, the system's effectiveness is gauged through key metrics like accuracy and precision.

A review of the literature was carried out to assess and contrast the currently available solutions in relation to the suggested solution. In the aspect of demographics identification and facial feature detection, research [4] highlights the potential of deep learning-based skin image analysis algorithms to enhance diagnostic accuracy and alleviate dermatologists' workload. While studies have explored acne diagnosis using deep learning algorithms, varying success rates have been observed. In [5] leverage AI-driven face recognition to diagnose diseases through facial phenotypes, achieving a combined sensitivity and specificity of 89% and 92%, respectively. Their introduction of "facial recognition intensity" introduces a new dimension to enhance accuracy. Furthermore, studies have delved into facial image classification, comparing techniques like convolutional neural networks (CNN) and support vector machines (SVM). Notably, this research [7] stands out for its ability to predict age and gender accurately, even with limited training data. Additionally, the comparison of facial image categorization algorithms [8] emphasizes the efficacy of predetermined algorithms and their implications. In [9] presents a MobileNet v2-based method for detecting various skin diseases, achieving impressive accuracy rates.

In the aspect of hair features detection, the research "ScalpEye for Scalp Health" [10] introduces ScalpEye, a deep

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learning-based system by Chang et al. sUsing ResNet and v2 Atrous Faster R-CNN models, it achieves accurate recognition (97.41%-99.09% precision) of four scalp hair signs, with potential enhancements planned, including more symptoms and larger sample sizes. In "SRoy and Protity [11]," a machine learning model predicts hair and scalp disorders (e.g., alopecia, folliculitis, psoriasis) with 96.2% training precision and 91.1% validation precision. The approach aids early identification and treatment of common hair and scalp issues.

The study by Ibrahim et al.[12] presents a pre-trained scalp condition classification method using image processing. Employing SVM, they categorized disorders via enhanced images, color/texture/shape features extraction, and edge detection, achieving scalp condition classification through extracted features. Comparing these studies, it's evident that the proposed solution in the literature review focuses on scalp and hair disease detection, particularly utilizing image processing and deep learning and techniques. The ScalpEye system [10] stands out due to its accurate recognition of hair signs and its subsequent use in the ScalpEye system for diagnosis. The results demonstrated a high degree of accuracy in detecting scalp conditions. Additionally, this section of the study offers a solution to the issue by using machine learning techniques to examine hair samples using data from mobile camera inputs. The accuracy and viability of such systems have not yet been thoroughly studied. The system's planned future improvements highlight the commitment to enhancing accuracy and scope.

In the aspect of skin features detection, [13]demonstrates the potential of pretrained CNN AlexNet in conjunction with SVM, achieving a remarkable 100% accuracy for three skin disease types, albeit with a limited training dataset. In [14] delve into image color and texture features, employing methods like image segmentation, Euclidean distance transformation, and GLCM-based feature extraction, resulting in 85%, 90%, and 95% accuracy for identifying three specific skin diseases. It is [15] emphasizes a fusion of classical machine learning and deep CNNs, training on a dataset of 10,000 images to achieve 95% accuracy in classifying six types of skin lesions.

In [16]proposes a mobile-based skin disease detection method utilizing TensorFlow and Keras, capable of identifying seven skin disease types with 87% accuracy. Srinivasu et al. [17] integrate MobileNet V2 and LSTM for skin disease classification, achieving 85.34% accuracy across seven lesion types using a texture-based approach

II. METHODOLOGY

A) Overall Product Recommendation Model

This intricate system involves multiple stages dedicated to skin, facial, and hair-related aspects, providing personalized recommendations for cosmetic products. The process commences by gathering data based on skin diseases and their severity, which is used to create models for identifying skin conditions and their seriousness using texture. The initial phase involves collecting pertinent information about skin diseases and severity to establish models capable of detecting skin issues and their level of severity. The subsequent stage follows a similar trajectory for facial data, encompassing the acquisition of facial skin condition-related data. This data is harnessed to construct models that can promptly detect faces in real-time video streams and ascertain facial skin conditions. Shifting the focus to hair-related aspects, the system amasses data centered around hair diseases and their severity, with texture and color as pivotal factors. This collected data forms the basis for fabricating models adept at recognizing hair ailments and gauging their severity.

Advancing to the final phase, the accumulated information serves as the bedrock for providing personalized cosmetic product recommendations. To facilitate this, a model is developed to detect skin types, requiring the collection of skin type-based data. This data is further enriched with reviews of cosmetic products, which are subsequently integrated into a product recommendation model. The operational process of the system is deliberately designed to be user-friendly and efficient. In the event of a skin concern, users can capture an image of the affected area. The image data is inputted into the skin type identification model, which identifies the specific skin type, such as oily or dry. This information is combined with results from sub-objectives, including skin disease identification, severity assessment, and facial condition recognition. The amalgamated data is utilized by the cosmetic product recommendation model to propose the most suitable cosmetic product tailored to the individual's unique needs.

B) Demographics Identification Model

The research employs a demographic identification model to ascertain the gender of users from facial images captured by the front camera of a smartphone. The model was constructed using Convolutional Neural Networks (CNN) and Keras framework. This model accepts individual images as input and predicts the gender associated with the image.

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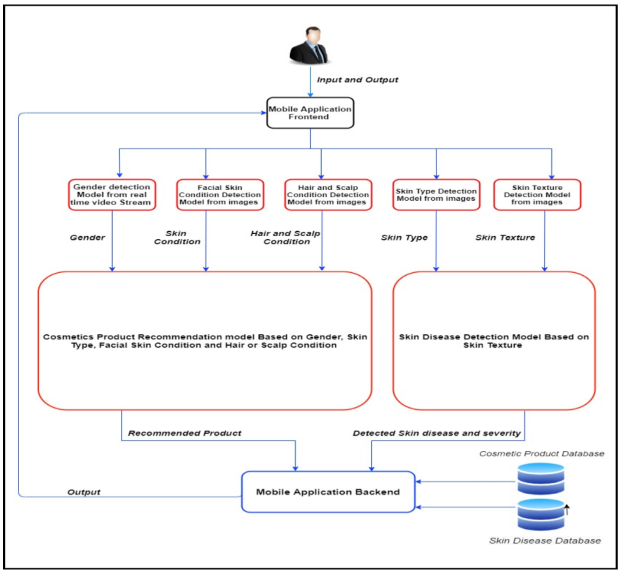

Figure 1: System Diagram 1

The application of this model requires data, and there are several open-source image data sets that can be used to train it. To train the model, The dataset underwent an initial division into training and testing datasets at an 80:20 ratio, followed by an 80:20 split of the training dataset into training and validation datasets.. There were approximately 1000 clear photos in all that CNN could be trained on.

C) Facial Features Detection Model

The implementation of the facial feature detection model involves identifying and examining faces within a live video stream or images. Its purpose is to recognize prevalent facial skin issues like acne, acne marks, blemishes, wrinkles, and dark circles. The model, created using Convolutional Neural Networks (CNN) in Keras, autonomously captures the user's facial image and generates an assessment of the facial condition. This assessment is then utilized to suggest products that are suitable for the user's current facial skin condition.

There are several open-source image data sets that can be used to train it. primarily using data from the Kaggle platform. Each of these data sets comprises of pictures that have been classified according to the conditions of the facial skin.Thisdatasetconsistsofapproximately5000, 512x512 sized face images with emotions such as acne, acne marks, stains, wrinkles, and black circles. The dataset was divided into an 80:20 ratio, with 80% allocated for training purposes. Subsequently, the training set was employed to instruct the neural network.

D) Hair and Scalp Condition Detection Model

The implementation of the hair disease detection model focuses on recognizing and examining facial images to identify prevalent hair-related conditions such as alopecia areata, dandruff, head lice, telogen effluvium, and tinea capitis. This model was built using convolutional neural networks, and the methodology entails gathering data specifically pertaining to hair diseases. This information is employed to develop the hair disease detection model based on both texture and color features. Users initiate the process by providing an image of their affected hair and scalp area. They then opt for the hair disease detection mode, which utilizes the hair disease detection model to identify potential hair diseases. If a potential hair disease is detected, the system further employs the detection model to assess the disease of the user's hair condition. This assessment is made by analyzing the texture and color of the affected area. Ultimately, the system presents the user with the name of the detected hair disease. The user is advised to seek appropriate medical attention based on these findings.

E) Skin Disease Detection Model

Utilizing either the smartphone's camera-captured image of the user's hand or a selected image from the device's image browser (Image files), a skin disease identification model is formulated to discern the user's specific skin conditions. The image is taken and fed to the model. The skin disease severity detection model uses prediction to suggest getting medical assistance based on the severity of the particular condition. CNN and Keras are both used to build the model.

Eczema, Melanoma, Atopic Dermatitis, Basal Cell Carcinoma, Melanocytic Nevi, and Benign Keratosis are six prevalent and frequent skin illnesses that are represented by the open-source dataset taken from Kaggle. The user's skin disorders were modeled using the CNN algorithm. A little over 5000 pictures taken between the ages of 20 and 75 were used to generate the model. About 1000 images from the dataset were used for each gesture, and these images were then standardized to a fixed size of 300*300 pixels. Images that had been preprocessed and standardized served as the model's training data.

Eighty percent of the dataset was allocated for training, with the remaining twenty percent designated for validation. The subsequent layers constitute the composition of this CNN. After the application of three successive convolutional layers with (3 x 3) filters, each comprising 32 and 64 layers respectively, a (2 x 2) max-pooling operation is implemented alongside a dropout layer. A SoftMax layer, containing a number of units equivalent to the class count for recognition, is incorporated, along with a fully connected layer consisting of 64 units. The Rectified Linear Unit (ReLU) serves as the chosen activation function in the initial fully connected layer and all subsequent convolutional layers. The categorical cross

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Entropy, the Adam optimizer, and the gradient descent method were used to train the weights.

F) Skin Type Detection Model

The complete system integrates a facial features detection model to assess real-time video streams or images, identifying common facial skin conditions such as acne, acne marks, stains, wrinkles, and black circles. This model, constructed with convolutional neural networks (CNN) using Keras to use images to detect skin type. These skin type recognitions guide suggestions for products tailored to users' current skin types. The skin type detection model is integral to the system, as skin type plays a pivotal role in cosmetic item recommendations.

For constructing the skin type detection model, open-source image datasets are pivotal, particularly from the Kaggle platform. These datasets are categorized based on diverse skin types. TensorFlow Libraries. The Cosmetic Product Suggestion Model employs the identified skin type from the skin type detection model and analyzes outputs from other sub-objectives to propose suitable cosmetic products. Recommendations draw from datasets comprising reviews, skin types, and skin conditions for cosmetic products, obtainable from the Kaggle website.

G) Skin Disease Severity DetectionModel

The skin disease severity model uses the output result of the skin disease detection model and uses texture-based analysis to detect the severity of the resulting skin disease. This model, constructed with Support Vector Machines (SVM) using SKlearn to use images to detect skin texture to detect disease severity.

For constructing the skin diseases severity model, open-source image datasets are used, particularly from the Kaggle platform. These datasets are categorized based on severity of skin diseases

III. RESULTS AND DISCUSSION

A) Results of Integrated Model

A refined personalized product recommendation model was developed, incorporating considerations for the user's gender, skin type, and current facial or hair condition. This inclusive model processes input images and generates tailored recommendations that are likely to pique the user's interest.

The model construction entailed the utilization of the KMeans algorithm, yielding a silhouette score of 0.4 and a within-set sum of square error amounting to 13168.02.

This model's distinctiveness lies in its ability to tailor recommendations by considering the user's gender, hair or skin condition, and notably, their specific skin type. This personalized approach empowers users to procure the most suitable products for their skin. Approximately 73% of the tested users express overall satisfaction with the suggestions, while 15% hold unfavorable opinions. A team of researchers has created an internet-based platform directed towards individuals with neutral or dissatisfied sentiments regarding product recommendations. The aim is to comprehensively comprehend their inclinations toward cosmetic products and demographic details. The model is then fed these data, and it will be periodically retrained. using the information gathered, it can perform better.

B) Demographic data identification model

The deep learning algorithm developed for identifying the user's gender underwent rigorous testing, revealing a Mean Absolute Error (MAE) of 1.2 on the test dataset. In terms of gender classification, the model demonstrated a commendable test accuracy of 90%.

Table I: Accuracy comparisons of demographicscation

Reference	Model	Accuracy (%)
[1]	Wide Residual Network	Age – 7.3(MAE)
[2]	CNN	Gender – 85%, Age – 73%
[3]	CNN	Gender – 84%, Age – 71%
Proposed method	CNN	Gender – 90%

In the gender classification task, both the male and female categories attained an F1 Score of 0.62. The "male" category demonstrated a precision of 0.96, whereas the "female" category showcased an accuracy of 0.94. Consequently, the gender classification procedure upheld a 90% accuracy rate.

Figure 2: Gender classification test on male photograph

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C) Facial Conditions Detection Model through an Input Image

We achieved higher accuracy in the Facial Conditions Detection model than in earlier research. Table II presents a comparison of outcomes with our trained model, which has an accuracy of 81.54%.

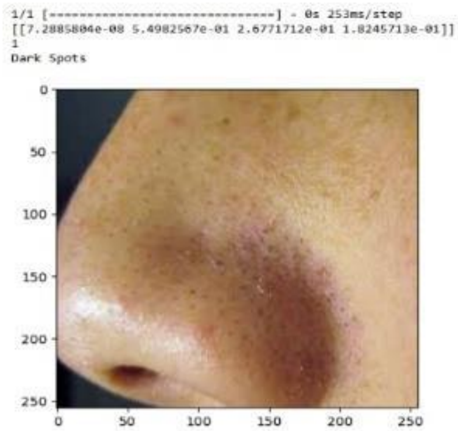

Figure 3: Output of a sample image from dataset where the persons Skin has dark spots

The Facial condition classification confusion matrix, shown in Fig. 4, interprets the overall classification of facial skin problems as average. When considering each class, the "Acne" class received the most correct classifications, followed by the "Dark Spots" and "Puffy Eyes" classes, and the "Wrinkles" class performed the least, owing to a lack of data availability for the "Wrinkles" class in the dataset that was chosen.

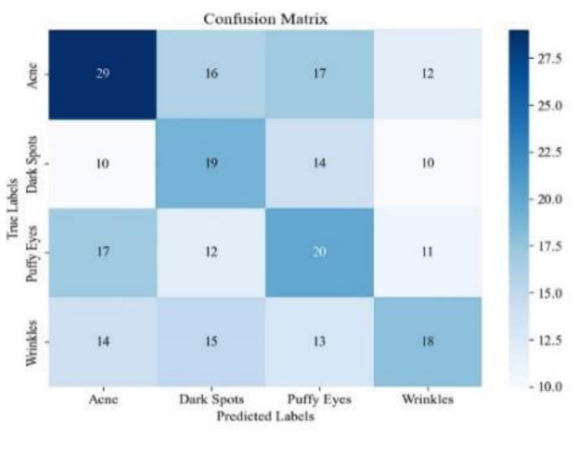

Figure 4: Confusion matrix of skin condition classification

Table II: Facial conditions detectional accuracy comparisons based on images

Reference	Model	Accuracy
[4]	CNN	68%
[5]	SVM	80%
Proposed method	CNN	81.54%

D) Hair and Scalp Disease Detection Model through an Input Image

The model developed for detecting Hair and Scalp Diseases exhibited a balanced performance, as reflected in its precision, recall, and F1 score. Nearly every class in the dataset achieved an F1 score of 0.74 or greater. The CNN-based model, utilizing the open-source Kaggle dataset, demonstrated an impressive accuracy of 98% in all implementations.

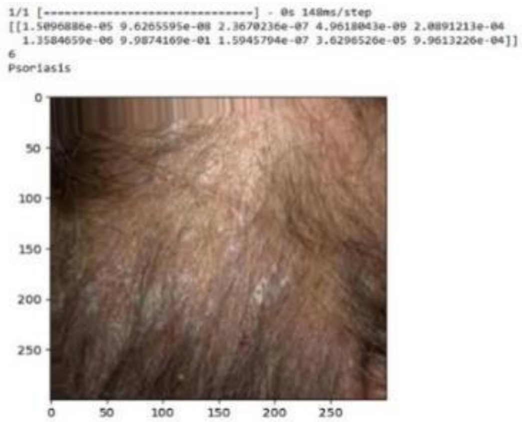

Figure 5: Output of a sample image from dataset where the person has psoriasis

The model developed for identifying Hair and Scalp Diseases has shown a balanced performance, as evidenced by its precision, recall, and F1 score. Nearly every category within the dataset achieved an F1 score of approximately 0.74. Moreover, the CNN-based model exhibited an accuracy of 98%. The entire model development process utilized the publicly available Kaggle dataset.

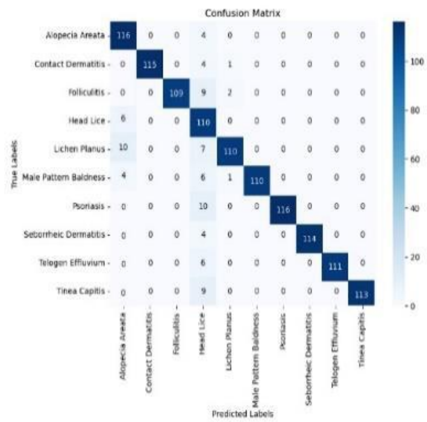

Figure 6: Confusion Matrix for hair and scalp diseases recognition model

Figure 6 depicts a confusion matrix for the hair and scalp disease recognition model, indicating that all categories perform extremely well in the classification.

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E) Skin Type Detection Model

In terms of skin type recognition, the CNN model utilized has obtained a training accuracy of 99% and a test accuracy of 90.62%.

Figure 7 exhibits a confusion matrix for the skin type recognition model, which shows that "Dry" skin type recognitions perform well in the classification process, while "Oily" skin type recognitions perform at a medium level.

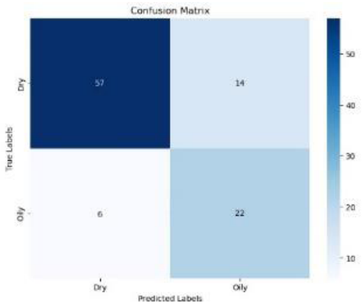

Figure 7: Confusion Matrix for skin type recognition

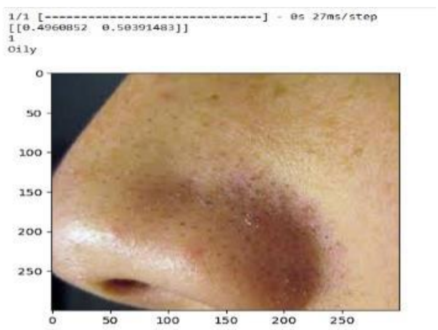

Figure 8: Testing skin type recognition model with a image of a person with oily skin

F) Skin Diseases Detection Model

Using visual input, a CNN model is trained to recognize the user's action. A wide range of skin illnesses are represented in the dataset. When the F1 Score of the model was considered, it achieved 0.5, and the model received an accuracy of 89% for the skin diseases detection model.

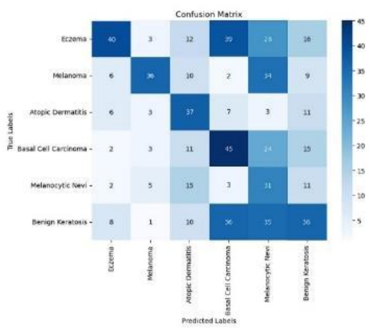

Figure 9: Confusion Matrix for skin diseases recognition

Table V: Activity recognition model accuracy comparison

Reference	Model	Accuracy
[13]	CNN	87.64%
[15]	CNN	68.5%
Proposed method	CNN	89%

The skin illnesses recognition confusion matrix (shown in Fig. 9) interprets the overall classification of facial skin problems as average. When each class is considered, the "Basal Cell Carcinoma" class has obtained the most correct classifications. All other classes performed well, with the exception of the "Melanocytic Nevi" class, which did poorly due to a lack of data for the "Melanocytic Nevi" class in the dataset used.

G) Skin Diseases Severity Detection Model

For the skin diseases severity detection, a SVM Model is trained using SKlearn. For this SVM Based model, an accuracy score of 60% was achieved. This SVM Based model analyses the spread of diseases by analyzing the texture of the given image First, the researchers used two types of SVMs, LBP and GLCM which gave accuracy results 60% and 43% accordingly. The LBP model was selected and used for this research as it achieved higher accuracy.

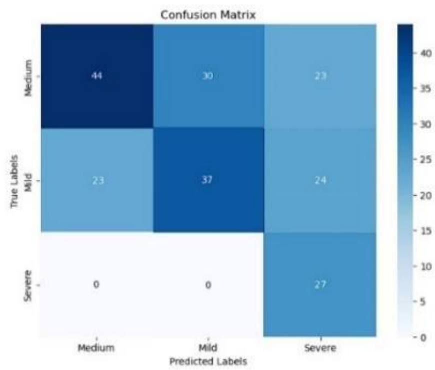

Figure 10: Confusion Matrix for skin diseases severity recognition

Table VI: Skin diseases severity detection model accuracy comparison

Reference	Model	Accuracy
[14]	CNN	50.24%
[17]	CNN	62.5%
Proposed method	SVM	60%

IV. CONCLUSION

This study primarily centers on the development of a gender-specific cosmetic product recommendation system, considering variables such as skin type, facial skin condition, as well as hair and scalp conditions to tailor personalized suggestions for users. Utilizing a hybrid machine learning methodology, our system incorporates unsupervised learning for suggestion components and supervised learning for gender, skin type, hair and scalp, as well as skin disease detection,

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including the severity assessment. K Means clustering used as unsupervised learning method to suggest products based on user reviews, skin type, facial skin condition and hair and scalp diseases. For skin type detection model, facial condition detection model, hair and scalp diseases detection model and skin diseases detection models used supervised CNN models. And the skin diseases severity detection model used supervised SVM techniques to detect severity of a recognized skin disease. After identifying the above data, the suggestion system suggests the most suitable product for the user. And also, the user can use the app to identify skin diseases which cannot be cured with cosmetic products. The only recognition model that averaged in this research was the skin diseases severity detection model which averaged at 60% of accuracy. All the other models performed well.

Future endeavors for this research will focus on enhancing the model's accuracy through increased data training. Additionally, there will be an emphasis on refining the user-friendly and dependable nature of the recommendation application.

REFERENCES

[1] A.De and A. Saha, “A comparative study on different approaches of real time human emotion recognition based on facial expression detection,” in 2015 International Conference on Advances in Computer Engineering and Applications, 2015, pp. 483–487.

[2] S. Gong, X. Liu, and A. K. Jain, “Jointly DE-biasing face recognition and demographic attribute estimation,” in Computer Vision – ECCV 2020, Cham: Springer International Publishing, 2020, pp. 330–347.

[3] A.Das, A. Dantcheva, and F. Bremond, “Mitigating bias in gender, age and ethnicity classification: A multi-task convolution neural network approach,” in Lecture Notes in Computer Science, Cham: Springer International Publishing, 2019, pp. 573–585.

[4] Huynh, Q. et al. (2022) “Automatic Acne Object Detection and Acne Severity Grading Using Smartphone Images and Artificial Intelligence,” Diagnostics, 12(8), p. 1879.

[5] Wu, D. et al. (2021) “Facial Recognition Intensity in Disease Diagnosis Using Automatic Facial Recognition,” Journal of Personalized Medicine, 11(11), p. 1172.

[6] J. Lemley, S. Abdul-Wahid and R. Andonie, "Comparison of Recent Machine Learning Techniques for Gender Recognition from Facial Images", 2016.

[7] G. Levi and T. Hassncer, “Age and gender classification using convolutional neural networks,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2015.

[8] B. Jaeger, W. Sleegers, and A. Evans, "Automated classification of demographics from face images: A tutorial and validation," Social and Personality Psychology Compass, vol. 14, (3), 2020.

[9] K. A. Muhaba, K. Dese, T. M. Aga, F. Zewdu, and G. L. Simegn, “Automatic skin disease diagnosis using deep learning from clinical image and patient information,” Skin Health and Disease, vol. 2, no. 1, Nov. 2021, doi: 10.1002/ski2.81.

[10] W. -J. Chang, L. -B. Chen, M. -C. Chen, Y. -C. Chiu and J. -Y. Lin, "ScalpEye: A Deep Learning-Based Scalp Hair Inspection and Diagnosis System for Scalp Health," in IEEE Access, vol. 8, pp. 134826-134837, 2020, doi: 10.1109/ACCESS.2020.3010847.

[11] Roy, M., & Protity, A. T. (2023). Hair and Scalp Disease Detection using Machine Learning and Image Processing. European Journal of Information Technologies and Computer Science, 3(1), 7–13.

[12] Ibrahim, S., Noor Azmy, Z. A., Abu Mangshor, N. N., Sabri, N., Ahmad Fadzil, A. F., & Ahmad, Z. (2020, October 1). Pre-trained classification of scalp conditions using image processing | Ibrahim | Indonesian Journal of Electrical Engineering and Computer Science. Pre-trained Classification of Scalp Conditions Using Image Processing | Ibrahim | Indonesian Journal of Electrical Engineering and Computer Science.

[13] N. S. Alk. ALEnezi, “A Method of Skin Disease Detection Using Image Processing And Machine Learning,” Procedia Computer Science, vol. 163, pp. 85–92, Jan. 2019, doi: 10.1016/j.procs.2019.12.090.

[14] L. Wei, Q. Gan, and T. Ji, “Skin Disease Recognition Method Based on Image Color and Texture Features,” Computational and Mathematical Methods in Medicine, vol. 2018, pp. 1–10, Aug. 2018, doi: 10.1155/2018/8145713.

[15] M. A. E.-H. Kassem, K. M. Hosny, R. Damaševičius, and M. M. Eltoukhy, “Machine Learning and Deep Learning Methods for Skin Lesion Classification and Diagnosis: A Systematic Review,” Diagnostics, vol. 11, no. 8, p. 1390, Jul. 2021, doi: 10.3390/diagnostics11081390.

[16] M. Maduranga and D. Nandasena, “Mobile-Based Skin Disease Diagnosis System Using Convolutional Neural Networks (CNN),” International Journal of Image, Graphics and Signal Processing, vol. 14, no. 3, pp. 47–57, Jun. 2022, doi: 10.5815/ijigsp.2022.03.05.

[17] P. N. Srinivasu, J. G. SivaSai, M. Ijaz, A. K. Bhoi, W. Kim, and J. D. Kang, “Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM,” Sensors, vol. 21, no. 8, p. 2852, Apr. 2021, doi: 10.3390/s21082852.

ISSN (online): 2581-3048
Volume 7, Issue 10, pp 503-510, October-2023
https://doi.org/10.47001/IRJIET/2023.710066

[18] Automatic Face & Gesture Recognition (FG 2017) - Rule-Based Facial Makeup Recommendation System | 10.1109/FG.2017.47. (n.d.). Sci-Hub | [IEEE 2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017) - Washington, DC, DC, USA (2017.5.30-2017.6.3)].

[19] Lin, T. Y., Chan, H. T., Hsia, C. H., & Lai, C. F. (2022, January 3). Facial Skincare Products' Recommendation with Computer Vision Technologies. MDPI.

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