Development Project 55-608850

Skincare Application report.

Your name: Tasnim Begum

Your student ID: C2005808

Your supervisor's name: Rizwana Rashad

Skincare Application: A Proof of Concept

Abstract

Many individuals encounter difficulties in selecting appropriate skincare products due to the extensive array of options available in the market. This challenge is particularly pronounced for individuals with brown and black skin, as the majority of skincare products are formulated with lighter skin tones in mind, resulting in issues such as hyperpigmentation and irritation. This paper introduces a proof-of-concept machine learning skincare application designed to identify a user's skin type (acne-prone, oily, dry) and recommend suitable products that are recognized for their safety and efficacy across all skin types, including those with higher melanin levels. The system seeks to enhance the accessibility and customization of skincare for diverse skin tones. This paper encompasses a literature review on skincare and machine learning applications, an analysis of ethical and legal considerations, and an evaluation of the system's effectiveness. (Buolamwini, J., & Gebru, T. (2018).

1. Introduction

Skincare is a growing industry, yet many consumers struggle to choose the right products because of the vast range available (Label Insight 2017). People with brown and black skin face unique challenges as many products are not formulated with their specific needs in mind (Taylor & Barbosa, 2020). The misuse of skincare products can lead to skin damage, irritation, and financial loss. This project aims to develop a proof-of-concept machine-learning-based application that determines a user's skin type and provides skincare recommendations that are safe for all skin types, particularly those with melanin-rich skin.

The primary objective was to improve users' skincare knowledge by offering accurate and inclusive recommendations. This report is structured as follows. Section 2 provides a literature review covering skincare challenges and machine learning applications. Section 3 presents legal, social, ethical, and professional considerations (LSEPI). Section 4 discusses an evaluation of the application, including the methodology, results, and findings. Finally, Section 5 suggests future improvements and Section 6 concludes the study.

2. Literature Review

2.1 The Challenges of Skincare Product Selection

Numerous consumers face difficulties in skincare owing to deceptive product assertions, ambiguity surrounding substances, and the vast selection of accessible choices. A study by Label Insight (2017) indicates that 81% of women do not fully comprehend the ingredients in personal care products, complicating the process of making informed decisions. Furthermore, individuals with darker skin tones necessitate products that address specific concerns such as hyperpigmentation, which are frequently neglected in mainstream skincare products (Taylor & Barbosa, 2020).

2.2 Machine Learning in Skincare

AI-driven skincare applications have been made possible by recent developments in machine learning. Skin condition analysis can benefit from the usage of Convolutional Neural Networks (CNNs), which are frequently employed for image classification jobs. In dermatology, previous studies have shown that deep learning models are useful for both detecting skin conditions and suggesting therapies (Esteva et al., 2017).

2.3 Skin Tone Representation in AI Models

In dermatology, artificial intelligence is being quickly incorporated for clinical diagnosis as well as patient-facing uses, such as virtual "try-on" and skincare analysis tools (Gordon et al., 2024).

The dataset's primary issue is under-representation. The quality and diversity of the huge datasets used to train AI models have a significant impact on how well they perform. One of the main problems is that photos of darker skin tones, including Fitzpatrick Skin Types (FST) V and VI, are significantly under-represented in these databases (Daneshjou et al., 2022; Guo et al., 2022). Black and Brown skin photos have historically been less common in dermatology textbooks and publicly accessible image repositories such as the International Skin Imaging Collaboration (ISIC). Much research conceals potential biases by failing to disclose the race, ethnicity, or skin type of subjects in their datasets. Skin type and ethnicity are different, and it is important to have a wide representation of skin types (Adelekun et al., 2021).

Due to this under-representation, AI models are biassed and perform noticeably worse on photos of people with darker skin tones than those with lighter complexion. This bias can impact a variety of AI applications, like skincare analysis, and is not only confined to medical diagnosis. Research on generic computer vision tasks has revealed bias against darker skin tones (Daneshjou et al., 2022).

According to the sources, AI solutions for customers are becoming progressively more common. For example, virtual "try-on" cosmetics and skincare analysis apps that can detect characteristics like pores or oiliness. The widespread problem of under-representation in dermatological image datasets strongly implies that these aesthetic tools may also experience decreased accuracy or biassed results when used by people with darker skin, similar to diagnostic models, even though the performance discrepancy for skincare analysis itself is not stated explicitly (Wen et al., 2022).

There are serious ethical questions about justice and inclusivity raised by AI's biassed performance as a result of under-representation. Since people of colour already experience discrepancies in dermatological care and results, it runs the danger of making already-existing healthcare disparities worse. According to (Mokoena et al. 2024) and (Gordon et al.2024), biassed AI technologies may put these communities at a greater disadvantage.

The varied Dermatology Images (DDI) dataset, which consists of images of FST V-VI with pathological confirmation, is one example of the varied datasets being created and used (Daneshjou et al., 2022). Reducing the performance difference between light and dark skin tones has been demonstrated to be possible through fine-tuning AI models on a variety of datasets, such as DDI. To increase fairness, other methods including adversarial debiasing, resampling, and data augmentation are also being investigated (Kamulegeya et al., 2023). More openness on the variety of datasets used to train AI models is demanded (Daneshjou et al., 2021).

2.4 Existing Skincare Applications

Recent years have seen the emergence of AI-powered skincare apps that provide users with individualised skin analyses and product recommendations based on image processing technologies. Numerous, commercial solutions, such as Haut.AI, YouCam Makeup, SkinVision, and Vichy Laboratoires Skin Consult AI, employ artificial intelligence to identify skin issues, forecast ageing, and match products. However, most of these apps cater to a wide range of users and often ignore the specific skincare problems that melanin-rich skin types of encounters.

SkinVision: This company intended for assessing the risk of skin cancer. It analyses mole patterns but does not provide acne diagnosis or basic skincare advice. (SkinVision. 2024)

YouCam Makeup: This focusses on beauty and makeup, offers basic skin condition analysis, including wrinkles and moisture, but it lacks medical confirmation for precise skin concerns.

Haut.AI: detects hydration, pigmentation, and UV damage using AI-trained models; but, without medical validation, its skincare suggestions are still restricted. (Haut.AI. 2025).

Vichy Skin Consult AI: Although the AI tool evaluates pigmentation changes and ageing markers and makes routine recommendations, its primary focus is on anti-aging issues rather than the diagnosis of acne or eczema. (Vichy Laboratoires. 2025.).

How This Proof-of-Concept Differs

Unlike existing tools, this project focuses on inclusive AI skincare recommendations, ensuring:

- Fairness in dermatology, prioritising accurate analysis for all people of colour.
- Hyperpigmentation detection (future development) to address brown and black skin concerns.
- Alignment with ethical AI standards (BCS & ACM) for responsible implementation.

2.4.1 Integration of Product Recommendations into the Application

Instead of using a dynamic algorithm, the skincare detection system currently uses a preset recommendation method. It classifies eczema and acne disorders into general product categories. To increase suggestion accuracy, future improvements might use user feedback and real-time algorithmic matching.

3. LSEPI Introduction.

AI-driven applications, particularly those that handle sensitive user data like skincare analysis photographs, must ensure compliance with legislative frameworks, address social inclusion and justice, follow ethical values, and retain professional accountability. These important factors are considered when designing this proof-of-concept system.

Legal Compliance (Data Protection)

Since noncompliance may lead to administrative fines or judicial penalties, data protection laws must be followed from the beginning (WIPO, 2021). Stricter security measures are needed because this system handles sensitive user photos that might contain health-related characteristics.

The developer chooses the means (how) and goals (why) of data processing in their capacity as the data controller. Third-party services, such as cloud providers, are considered data processors when they process user data, necessitating contractual agreements outlining security obligations (Usercentrics, 2025).

Controllers must follow fundamental data protection principles, including:

- Lawfulness, equity, and openness → User consent, for example, must be freely provided, particular, and informed in order for processing to have a legitimate legal basis (WIPO, 2021). Accessible information and unambiguous privacy policies provide transparency (Women Who Code, 2024.).

- Limitation of purpose: Information must only be gathered for specific, justifiable purposes. Anonymisation or new consent are necessary for any secondary use, such as using health data for insurance profiling (Public Health England, 2017).
- Accuracy and data minimisation: Only necessary personal information should be gathered. The system should work without identifying information if it can. In order to avoid making incorrect recommendations, user data should be able to be corrected (WIPO, 2021).
- Storage restriction and security: Personal information must be protected via encryption, pseudonymization, and other industry standards, and it must not be kept for longer than is necessary (Women Who Code, 2024).

A Data Protection Impact Assessment (DPIA) may be required by law to evaluate hazards and support processing decisions because this system uses AI-driven image processing (Out-Law/Pinsent Masons, 2024). A Data Protection Officer (DPO) may also need to be appointed in situations involving extensive processing of sensitive data (Usercentrics, 2025).

Social and Inclusivity Considerations

Everyone should have equitable access to technology. However, it is frequently the case that AI models that have been trained on biassed datasets do not perform uniformly across skin tones (Daneshjou et al., 2022). By combining a variety of datasets, including Roboflow, this approach actively reduces bias and guarantees equal representation in skincare recommendations.

Whether because of algorithmic bias, economic inequality, or physical limitations, computing professionals are urged to avoid exclusion (Bryant, 2024). Systems that affect health outcomes need to take human values and fair access into account in addition to technical precision (Kamulegeya et al., 2023).

Ethical Considerations

Transparency, dependability, and equity are needed for AI-powered skincare advice. Among the ethical issues are:

- Preventing harm: Users shouldn't be misled by unreliable dermatological advice from AI-based skincare analysis (ACM, 2018).
- Algorithm accountability: AI forecasts need to be supported by data to reduce risks such as false negatives in the identification of skin conditions (Gordon et al., 2024).
- Continuous risk assessments: To guarantee ethical and secure implementation, AI should be regularly reevaluated (Mokoena et al., 2024).

Best practices are outlined in the ACM Code of Ethics, which emphasises that AI systems should minimise unintended harm, operate transparently, and be subject to ongoing risk assessment (ACM, 2018).

Professional Responsibility

AI applications should be guided by ethical development principles since software engineers are trusted by the public (BCS, 2025). Among the responsibilities of a professional are: To guarantee accuracy, thorough testing, debugging, and review are required (IEEE-CS/ACM, 1999). handling data ethically and making sure that datasets represent a range of demographics (Kamulegeya et al., 2023). participation of stakeholders, such as data protection specialists, ethicists, and dermatologists (Bryant, 2024).

The responsible deployment of AI is reinforced by the fact that this system is a proof-of-concept and should never be confused with a professional dermatological consultation (Public Health England, 2017). Compliance, equity, and dependability should continue to be top concerns as the sector develops (Regulation (EU) 2017/745, 2017.).

Final Thoughts

Although AI in skincare has the potential to revolutionise the industry, it needs strict ethical, legal, and professional safeguards to guarantee inclusivity, fairness, and transparency. This proof-of-concept system aims to create AI in an ethical and responsible manner by incorporating a variety of datasets, improving privacy safeguards, and abiding by professional norms of conduct.

4. Evaluation

4.1 Evaluation Methodology

In order to provide an objective evaluation of the model across a wide range of photos, this proof-of-concept application was tested using a test dataset obtained from Roboflow. Among the evaluation metrics used were:

- Analysis of Precision and Recall, which assessed how reliable AI detection was.
- The total categorisation performance was evaluated using Mean Average Precision (mAP) ratings.
- Examining the effects of contrast enhancement, which assessed enhancements in darker skin tone detection.

Future evaluations would need to incorporate user feedback and improve identification accuracy by taking into account actual skincare issues. Also, clinical validation trials, which guarantee AI suggestions validated by dermatologists.

4.2 Results and Findings

Model detection rates varied across different conditions:

- Acne Detection: Precision: 31.2%, Recall: 16.4%, mAP50: 13.6%
- Eczema Detection: Precision: 36.2%, Recall: 13.6%, mAP50: 14.9%

The following issues were noted were low recall rates for eczema and acne, especially mild case misclassification. There was also bias in the dataset, as training samples tended to have lighter skin tones.

Key findings included:

- If contrast enhancement was implemented it would've moderately improved detection on darker skin, but model fairness remains an issue.
- Diversity in the dataset has a direct effect on classification success, highlighting the necessity of more skin tone representation.
- Although the recommendations were predicated on preset regimens, future accuracy enhancements could consider specific skincare considerations.
- Limitations of Preset Skincare Recommendations: The model depends on predetermined skincare regimens that might not take environmental influences or individual skin sensitivity into consideration. Personalised suggestions must be incorporated into future improvements. Even though the products chosen are known to be safe, some people may still be sensitive.

5. Future Improvements

Future advancements in AI skincare detection might involve possible dataset extension, improving the representation of brown and black skin tones for fairness. Improvements to model training that use datasets evaluated by dermatologists. Developing mobile applications to enhance accessibility and track skin conditions in real time.

6. Conclusion

In conclusion the feasibility of AI-powered skincare detection in improving accessibility and inclusivity in dermatology is demonstrated by this proof-of-concept project. The approach makes a significant contribution to closing representation gaps in skincare recommendations for melanin-rich skin tones by combining several datasets and utilising machine learning techniques.

But there are still issues, especially with model validation, fairness, and bias mitigation. Expanded datasets, dermatologist-led validation, and algorithmic improvements that take into consideration a wider range of skincare issues could greatly increase the system's efficacy.

To guarantee safe, moral, and efficient skincare products future advancements should concentrate on improving recommendation accuracy, strengthen detecting algorithms and integrating actual user input. With these developments, an AI system could make a significant contribution to help the skincare industry with equitable skincare accessibility and personalised dermatology for all users. This would overall make people more aware and knowledgeable about their own needs, creating more confident individuals especially for people of colour.

References

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. Conference on Fairness, Accountability, and Transparency, 77–91.
https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Buolamwini%2C+J.%2C+%26+Gebru%2C+T.+%282018%29.+Gender+shades%3A+Intersectional+accuracy+disparities+in+commercial+gender+classification.+Conference+on+Fairness%2C+Accountability%2C+and+Transparency%2C+77%E2%80%9391.&btnG=#d=gs_qabs&t=1740601428740&u=%23p%3D1tXhpvVwic8J

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118.
https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Esteva%2C+A.%2C+Kuprel%2C+B.%2C+Novoa%2C+R.+A.%2C+Ko%2C+J.%2C+Swetter%2C+S.+M.%2C+Blau%2C+H.+M.%2C+%26+Thrun%2C+S.+%282017%29.+Dermatologist-level+classification+of+skin+cancer+with+deep+neural+networks.+Nature%2C+542%287639%29%2C+115-118.&btnG=#d=gs_qabs&t=1740601509646&u=%23p%3DsG6aADprOGMJ

European Parliament. (2016). Regulation (EU) 2016/679 (General Data Protection Regulation). Official Journal of the European Union.
https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=European+Parliament.+%282016%29.+Regulation+%28EU%29+2016%2F679+%28General+Data+Protection+Regulation%29.+Official+Journal+of+the+European+Union.&btnG=#d=gs_qabs&t=1740601926154&u=%23p%3DWar_4I6dM80J

Label Insight. (2017, July 25). Study: Confusion over ingredients in personal care products impacts female buying behaviour. PR Newswire. https://www.prnewswire.com/news-releases/study-confusion-over-ingredients-in-personal-care-products-impacts-female-buying-behavior-300495267.html

Taylor, S. C., & Barbosa, V. (2020). Hyperpigmentation and photodamage in skin of colour: A review and practical approach. Journal of Clinical and Aesthetic Dermatology, 13(6), 31-41. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7069578/

CeraVe. (2025). About CeraVe: Pioneers in Skincare Science. Retrieved from https://www.cerave.com/about-cerave

Acnecide. (2025). Acnecide+Purifide. Retrieved from https://acnecide.co.uk

Marie Claire UK. (2021). CeraVe - Everything to Know About the Skincare Brand Dermatologists Love. Retrieved from https://www.marieclaire.co.uk/beauty/skincare/cerave-uk-skincare-707607

New York Post. (2021). Google wants to diagnose your skin condition. Retrieved from https://nypost.com/2021/05/19/google-wants-to-use-ai-to-diagnose-your-skin-condition/

Dr V. Vanita Rattan. (2025). *The Science of Skin of Colour*., Retrieved from https://www.skincarebydrv.com/pages/skincare-for-skin-of-colour.

UK Government. (2018). *UK Data Protection Act 2018*. Retrieved from https://www.legislation.gov.uk/ukpga/2018/12/contents/enacted

Perfect Corp. (n.d.). *AI Skin Diagnostic: How AI is changing skin analysis*. Retrieved, from https://www.perfectcorp.com/business/video/73

SkinVision. (2024). *AI-Powered Skin Cancer Risk Assessment*. Retrieved, from https://www.skinvision.com/

Haut.AI. (2025). *Exploring the potential of AI-enhanced skincare diagnostics*. Retrieved, from https://haut.ai/blog/tpost/05kel00m41-exploring-the-potential-of-ai-enhanced-f

Vichy Laboratoires. (n.d.). *Here's how to use AI to tackle the seven signs of skin aging*. Retrieved, from https://www.vichy.ca/en_CA/heres-how-to-use-ai-to-tackle-the-seven-signs-of-skin-aging.html

Adelekun, A., Onyekaba, G., & Lipoff, J. B. (2021). Skin color in dermatology textbooks: An updated evaluation and analysis. *Journal of the American Academy of Dermatology*, *84*(1), 194–196. https://doi.org/10.1016/j.jaad.2020.04.084

Daneshjou, R., Barata, C., Betz-Stablein, B., Cai, CY., Celebi, M. E., Codella, N. C. F., Combalia, M., Fleming, P., Granter, S. R., Gutman, D. A., Halpern, A. C., Harmon, S. A., Helba, B., Hofmann-Wellenhof, R., Janda, M., Kassamali, B., Kittler, H., Kose, K., Lee, O., ... Rotemberg, V. (2022). Checklist for Evaluation of Image-Based Artificial Intelligence Reports in Dermatology: CLEAR Derm Consensus Guidelines From the International Skin Imaging Collaboration Artificial Intelligence Working Group. *JAMA Dermatology*, *158*(1), 90–96. https://doi.org/10.1001/jamadermatol.2021.4915

Daneshjou, R., Smith, M. P., Sun, M. D., Rotemberg, V., Zou, J., Kolachalama, V. B., & Kumar, A. (2022). Disparities in dermatology AI performance on a diverse, curated clinical image set. *Science Advances*, *8*(31), eabq6147. https://doi.org/10.1126/sciadv.abq6147

Daneshjou, R., Smith, M. P., Sun, M. D., Rotemberg, V., & Zou, J. (2021). Lack of transparency and potential bias in artificial intelligence data sets and algorithms: A scoping review. *JAMA Dermatology*, *157*(11), 1362–1369. https://doi.org/10.1001/jamadermatol.2021.3129

Gordon, E. R., Trager, M. H., Kontos, D., Weng, C., Geskin, L. J., Dugdale, L. S., & Samie, F. H. (2024). Ethical considerations for artificial intelligence in dermatology: a scoping review. *British Journal of Dermatology*, *190*(6), 789–797. https://doi.org/10.1093/bjd/ljae040

Guo, L. N., Lee, M. S., Kassamali, B., Mita, C., & Nambudiri, V. E. (2022). Bias in, bias out: Underreporting and underrepresentation of diverse skin types in machine learning research for skin cancer detection-A scoping review. *Journal of the American Academy of Dermatology*, *87*(1), 157–159. https://doi.org/10.1016/j.jaad.2021.06.884

Kamulegeya, L., Kwizera, H., Ntaro, M., & Alii, A. N. (2023). Using artificial intelligence on dermatology conditions in Uganda: A case for diversity in training data sets for machine learning. *African Health Sciences*, *23*(2), 753–763. https://doi.org/10.4314/ahs.v23i2.86

Mokoena, L. S., Mndzebele, N. L., Ndhlalambi, L. S., & Shoala, M. A. (2024). Skin Type Diversity in Skin Lesion Datasets: A Review. *Journal of Medical Systems*, *48*(3), 26. https://doi.org/10.1007/s13671-024-00440-0

Wen, D., Khan, S. M., Xu, A. J., Ibrahim, H., Smith, L., Caballero, J., Perez, C. de B., Denniston, A. K., Liu, X., & Matin, R. N. (2022). Characteristics of publicly available skin cancer image datasets: a systematic review. *The Lancet Digital Health*, *4*(1), e64–e74. https://doi.org/10.1016/S2589-7500(21)00252-1

BCS, The Chartered Institute for IT. (2025). *BCS code of conduct*. BCS. https://www.bcs.org/membership-and-registrations/become-a-member/bcs-code-of-conduct/

Bryant, K. (2024, March 22). *Bridging the digital gap: Tech's role in social responsibility*. Forbes. https://www.forbes.com/sites/kalinabryant/2024/03/22/bridging-the-digital-gap-techs-role-in-social-responsibility/

Association for Computing Machinery. (2018). *ACM code of ethics and professional conduct*. ACM. https://www.acm.org/binaries/content/assets/public-policy/usacm/e-voting/letters/usacm_tgdc.pdf

IEEE-CS/ACM Joint Task Force on Software Engineering Ethics and Professional Practices. (1999). *Code of ethics for software engineers*. IEEE Computer Society. https://www.acm.org/code-of-ethics/software-engineering-code

Out-Law/Pinsent Masons. (2024, July 24). *Compliance risks need to be considered to harness the power of wellness apps*. Out-Law. https://www.pinsentmasons.com/out-law/news/compliance-risks-considered-wellness-apps

Public Health England. (2017, October 9). *Criteria for health app assessment*. GOV.UK. https://www.gov.uk/government/publications/health-app-assessment-criteria/criteria-for-health-app-assessment

Usercentrics. (2025, January 28). *Mobile apps and GDPR violations: Who has been fined?* https://usercentrics.com/knowledge-hub/mobile-apps-and-gdpr-violations-who-has-been-fined/#:~:text=To%20date%2C%20as%20of%20early,WhatsApp%2C%20for%20EUR%201.2%20billion.&text=Find%20out%20how%20user%20consent,with%20your%20automation%20and%20monetization

Wikipedia contributors. (2017). *Regulation (EU) 2017/745*. In *Wikipedia*. Retrieved, from https://en.wikipedia.org/w/index.php?title=Regulation_(EU)_2017/745&oldid=1274008005

Women Who Code. (2024). *Guarding user data in mobile apps: Best practices for security*. wwc. https://womenwhocode.com/blog/guarding-user-data-in-mobile-apps-best-practices-for-security

WIPO. (2021). *A guide to data protection in mobile applications*. WIPO. https://www.wipo.int/export/sites/www/ip-development/en/agenda/docs/wipo-guide-data-protection-mobile-apps.pdf