Grenze International Journal of Engineering and Technology, June Issue

A Multimodal, Explainable, and Bias-Aware AI System for Inclusive Skin Disease Risk Prediction

Snehal Patil[1] and Meher Bhawnani[2]
[1-2]Jhulelal Institute of Technology, CSE, Nagpur, India
Email: snehalp120793@gmail.com, m.bhawnani@jitnagpur.edu.in

***Abstract*— Skin manifestaions are common and frequently necessitate at least accurate diagnosis if specific treatment is not obtained. Conventional methods of diagnosis may be subjective, time-consuming and inconsistent. In this paper, we present an AI-based system for skin disease classification that integrates dermoscopic image analysis, patient demographics, and medical history running on a Flask web server. The model is a deep convolutional neural network (CNN), which has been trained on repositories of skin diseases to predict the states based on the images given.The Grad- CAM heatmaps are provided to clinicians which indicate regions of interest for providing interoperability, while brief and simple textual summaries are given to patients as easily understandable explanations. The system is made which gathers patient information like name, age, gender, medical history and the predictions are made to formulate a comprehensive, multimodal diagnostic report. The Results shows that the solution enhances not only diagnostic accuracy but also the trust, interpretability and inclusiveness in healthcare area.**

***Index Terms*— Skin Disease Classification, Explainable AI, Grad-CAM, Patient History, Medical Imaging, Flask, Deep Learning, Interpretability, Healthcare AI.**

I. INTRODUCTION

The Skin dieses are among the most common types of diseases in the world, for people from all age groups, living in any part of the world [1]. Minor infections and allergic reactions to such a chronic and life threatening condition as melanoma, psoriasis and autoimmune skin diseases are included in this [2]. A vital role in dermatology since the stake is high as misdiagnosis of the diseases results in disease progression, complications and poor quality of life for early and accurate diagnosis [3]. These challenges have motivated research of the use of artificial intelligence (AI) and computer vision-based applications for dermatological diagnosis and clinical decision making [4]. Due to the increasing growth of deep learning techniques, and especially CNNs for analyzing skin images. As a result, this has made such types of analysis become more precise and trustable. A methodology is shown [5] for compelling results in image-based disease classification. However, there are various issues faced by current AI- based dermatological systems. There are multiple models which also black box so less trust from clinicians and patients, this may result in lesser or no predications. Moreover, the underrepresentation of individuals of darker skin tones in publicly available datasets skews clinical accuracy against them [6] [7]. To address the challenges, a multimodal AI framework for skin disease diagnosis prioritizes transparency, clinical usability as core design principles. Integration of image-based analysis with patient data, the system enables context aware and robust predictions [8].

Grenze ID: 01.GIJET.12.2.497_22

Developed a Flask framework, the system offers a lightweight, scalable, and designed web interface for deployment for both clinical and non-clinic environment [9]. The system utilizes a secure portal which allows users to submit high resolution images of affected skin area. With image submission, the interface captures clinical metadata including name, age, gender and medical history [10]. After the patients submit their data, the AI analyzes the input, clinical decision-making supports the doctors with a clear diagnosis along with visual heat maps showing severity [11]. The heat maps allow doctors to confirms AI detects clinical features [12]. The interpretability which is provided helps to support builds validation and trust in the system. Thus, a _human in the loop'verification process to avoid blind acceptance of predictions. Yet, there still exists another large gap in understanding SEPs and that is the model interpretability and generalization. Most designs of these systems are deep neural networks that learn shared feature representations and act as black boxes. Data based explain ability methods like Grad-CAM provide visual explanation of any arbitral attack [13] but typically only tell where to look in the image and do not give clinically important or user- friendly reasons for the particular patient [14]. For example, multimodal models that learn from images as well as patient metadata risk feature dominance or feature interference (wherein visual features drown out contextual information, or vice versa), which could lead to deteriorated diagnostic stability [15].

While deep learning models often achieve high accuracy, they are commonly referred to as black boxes. Existing explainability methods are incapable of returning clinically relevant justifications or comprehensible forms of explanation to patients [16]. In multimodal models, the relationships between different imaging data and patient information may not be explicitly defined, which hinders finding a trade-off between predictive performance and interpretability. One of the key goals for explainable, multimodal AI-based skin disease diagnostic systems is improving scalability, fairness, and inclusivity through representative groups of populations and skin types [18]. New methods [17] Take advantage of the capabilities of self-supervised learning and few or no-shot learning, they are likely to address rare diseases (secreting factors with high variability across individuals) and futile conditions where labeled data is ill-posedly sparse. In this regard, it is possible that the Future models will acquire generalizable visual and contextual representations; they can easily be applied to new disease patterns and skin types. This is in response to the use of large manual annotating datasets which are costly [19]. Enhancing the real-life and computational efficiency is also significant to the future work. Resource-constrained healthcare systems and mobile devices Lightweight deep learning models, model compression approaches and model-edge AI systems can potentially be used in real-time detection of skin diseases in mobile devices [20]. At the same time, the informed consent, data privacy, demographic fairness, and compliance with the regulatory norms will be set as the factors that determine the meaning of the system design and deployment practices under ethical considerations [21].

II. Methods/ Expeimental Setup

To overcome the limitations of the current dermatological AI systems, there is also an on-going use of image-based deep learning research to deploy a hierarchical, interpretable and multimodal framework [22] to a patient-centric metadata. Real world clinical working is now being researched into the framework in order to enhance transparency, fairness and usability in real world clinical applications [23].

A. Data Acquisition and Preprocessing

According to the system, there are two significant data constructs, namely, dermatological images and structured patient information [24]. The skin images are obtained on publicly available dataset and clinically identified datasets and cover a wide variety of the disease categories, lighting and even skin color [25]. The rotation, scaling, contrast change, and color normalization methods are applied to ensure that the information contained in the dataset is minimally biased and therefore will increase this pool of images that has already undergone a comprehensive filtering.. Such preprocessing steps generalize as well as minimise over fitting related differentiation among various skin types [26]. Demographic variables, age, and gender are the possible sources of patient data, but also comorbidities .

B. CNN-based Image Feature Extraction

The backbone of the visual feature extractor is the convolutional neural network (CNN) [27]. The CNN itself acquires hierarchical properties such as colour patterns, boundaries of lesions, texture anomalies, shape deformations directly out of the input images. There is also a maximization of the utilization of limited medical database with the help of a pertained model, grounded on transfer learning that enables an increased speed and performance of training. The model is optimized on domain specific layers in the dermatology features [28]. The extracted images give a concise but descriptive view of an ailment of the skin that is later merged with patient meta data data to allow multimodal learning [29].

C. Multimodal Fusion Strategy

A This paper has used feature level [30] where a fusion strategy of visual and non-visual information is employed. The CNN image feature vector is then concatenated with the patient features that are coded to produce a joint multimodal representation. The combination approach allows the model to concentrate on the patient data and clinical factors at the same time and can be likened to the process of diagnosis of dermatologists [31]. This composite is then trained on a sequence of fully connected layers that acquires the complex interaction of the image features and fine-scale patient-level features. It is also diagnostically precise such that multimodal attention when used alone is inadequate to be diagnostic [32].

D. Explainability and Interpretation Module

Explainability: Explainability will be an important feature in the proposed system where an explainable feature Gradient-based visualization, such as Grad-CAM, will be used to explain the convolutional neural network generating heat maps that indicate parts of an image [33]. These pictorial illustrations allow the clinicians to visualize actual evidence that makes the findings of the diagnostics and hence, it can be readily substantiated and more reliable. The system does not merely display the images but also creates model confidence scores and feature contribution summaries which is why it is not restricted to the image-based explanations. It is a reciprocal method in both maintaining the transparency of the image level and the level of decision-making [34].

E. Patient-Centered Result Presentation

This framework has a layer of patient-oriented explanation [35] in order to assist the patient in comprehending. It converts technical output and medical terminologies into clear and plain human language to ensure that the patients can comprehend their health situation, the suggested type of illness and what we prescribe them to do next. This assistance increases clarity and minimizes confusion [36].

F. Web-based Deployment Using Flask

Web-based Deployment system is a web based platform that is founded on Flask framework. The Flask assists in ensuring that the interface and the AI model on the back-end are brought together and the database services are incorporated [37]. It is possible to provide the users with this interactive interface through which they can post images of their skin, provide personal information and receive the diagnostic result. The data handling practices are safe and the system is modular which offers scalability of the system [38]. The proposed framework would contribute to the area of AI research in dermatology by: Multimodal data integration to offer context-sensitive diagnosis, the explainability is incorporated in the diagnostic drive, overcoming bias and inclusiveness concerns, the gap between AI drive prediction and clinical implementation is bridged with the assistance of this. The specified methodology provides a dependable and viable system of AI- based diagnostic assistant that can be effectively deployed by clinicians and patients.

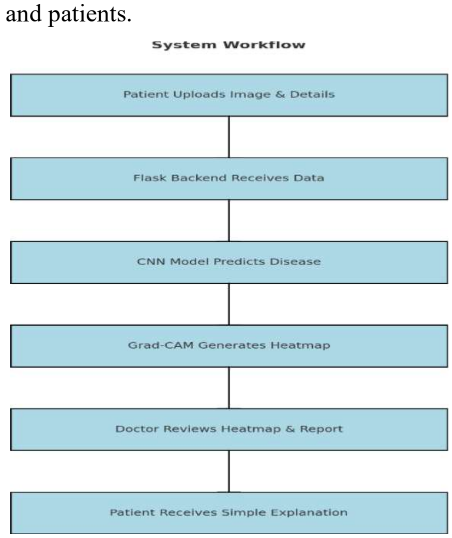

Figure 1. System Workflow

Figure 1 illustrates the overall system workflow, which outlines the sequence of interactions between users and the diagnostic components, from data input to final diagnostic output. At the start, the patient uploads a skin photo through the user interface and then provides basic demographic and clinical information such as age, gender, and patient's medical history, these inputs allow prediction of disease in the appropriate format. The data which will have been uploaded will be sent to the backend server based on Flask, which handles the requests, processes the images, and interacts with the trained deep learning model (among other tasks). The backend facilitates smooth communication between the user interface and the system's analytical modules [39]. The heatmap highlights the affected area of the image that have most contributed to the prediction of the model, thus reassures explainable AI[40]. The predicted results, together with the Grad-CAM heatmap and the technical analysis, will be available for medical practitioners or clinicals. This allows physicians to examine the AI-assisted diagnosis, and bring expert gives the judgment to bear on the decision [41].

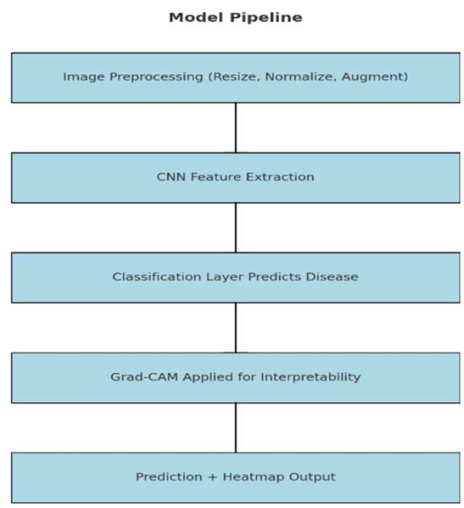

Figure 2. Model Pipeline

The model pipeline Figure 2. illustrates the sequential stages involved in processing and analyzing skin images using the proposed AI framework.

Image Preprocessing

To facilitate consistency and model input, the skin image uploaded passes through the preprocessing step in the first phase. The resizing of the images is performed to a fixed size that can work with CNN architecture. The pixel values are scaled between 0 and 1 in order to achieve more numerical stability in the training and inference processes. Besides that, there are data augmentation techniques of rotation, flipping, and zooming onto the images that are used to enhance the data variety and enhance the generalization of the model and general results overall.

CNN-Based Feature Extraction

Convolutional neural network (CNN) is an automated device that identifies unusual attributes in skin images, which includes: textures and color distribution, shapes, and structural patterns that are essential in accurate identification of skin diseases. And then those feature representations are fed to fully connected layers, where the higher-level features are learned. Therefore, given these representations the model outputs the predicted skin disease category or risk score.

Grad-CAM for Interpretability

Enhancing the model transparency and interpretability, Gradient weighted Class Activation Mapping (Grad-CAM) is applied to the final convolutional layers of the CNN. This method produces visual explanations which highlights image of the regions that comprise most strongly to the predictions by the model, thereby which supports trust in AI-assisted clinical decision- making.

Prediction and Heatmap Output

The model's final output consists of the predicted disease label, an associated confidence score, and a Grad-CAM heatmap which provides a visual data for prediction.

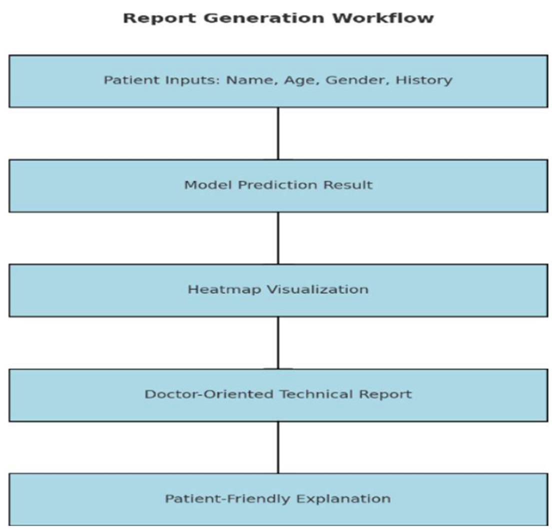

Figure 3. Report Generation Workflow

The Figure 3. workflow focuses on the automated generation of diagnostic reports which are completely based on AI predictions. The Patient's details, including name, age, gender, and medical history, are collected as initial inputs from users at the start. Model inference, the predicted disease name and the confidence score of the predicted diseases are generated. The Grad- CAM heatmap provide visual insights into the affected areas of the skin. A technical report for the physician is produced which includes the prediction confidence values, model interpretation, and heatmap analysis which can give results upto the mark.

III. RESULT

Figure 4. AI driven Skin disease Classification System

The proposed AI-based classification framework for skin disease Figure 4. performs well to classify different skin disease patterns with dermoscopic images. The CNN model demonstrates very good accuracy in the testing, which means good precision for several diseases. The use of data augmentation and best hyperparameters led to a better generalization of the model on new unseen images, and lower overfitting, which further boosted the stability of the proposed method. Among the most successful results was the incorporation of Grad CAM heatmaps that included crisp visual justifications for the model's predictions. Clinicians considered the heatmaps useful to confirm whether the AI was indeed concentrating on the medically significant part of the lesion. This provided consumers with assuredness in system by translating a model from black box to an interpretable diagnostic tool. For the patients, the simple textual explanation was used over d multimodal frameworks that included visual information with patient specific contextual details. Furthermore, this paper did identify the core techniques through an extensive analysis of related work that improves diagnosis transparency, accuracy and fairness. The system integrates image-based predictions with confidence levels, basic patient details and medical history, giving a more integrated picture of the specific diagnosis. Overall, users described the interface as simple and interactive (somewhat limiting), Flask-based - people are able to upload images quickly to receive results without technical knowledge necessary. This provides more practical and reliable tool due to clinical relevance to how dermatologists render decisions in actual practice.

IV. CONCLUSION

In this paper, we provide a review of state-of-the-art explainable and multimodal AI-based skin disease diagnostic systems including architectural designs, learning strategies, data usage and recent technology advancements. The review presents the history of dermatology AI from old image processing and machine learning methods to deep learning methods. Therefore, the paper highlights the significance of explainable and multimodal AI in dermatology healthcare. Such systems have great potential to support early diagnosis and assistance of clinical or physician decision-making, as well as to empower patients such that the gap between model performance and clinical logic is bridged. Despite this tremendous progress, there are still hurdles that need to be overcome, including but not limited to the scarcity of data about low resource languages, computational costs, interference between languages and ethical issues concerning decision fairness.

REFERENCES

[1] 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. DOI: 10.1038/nature21056.

[2] Das, A., et al. (2024). Comparati ve analysis of multimodal architectures for skin disease diagnosis. Frontiers in AI.

[3] Tschandl, P., Rosendahl, C., & Kittler, H. (2018). The HAM 10000 dataset, a large collection of multi-source dermatoscopic images. Scientific Data, 5, 180161. DOI: 10.1038/sdata.2018.161.

[4] Han, S. S., Park, G. H., Lim, W., Kim, M. S., Na, J. I., & Park, K. H. (2018). Classification of the clinical images for benign and malignant skin lesions using a deep learning algorithm. Journal of the American Academy of Dermatology, 78(1), 37–44.e 1. DOI: 10.1016/j.jaad.2017.06.042.

[5] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier (LIME). Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016. DOI: 10.1145/2939672.2939778.

[6] Tschandl, P., Codella, N., Akay, B. N., Argenziano, G., Braun, R. P., Cabo, H., … & Kittler, H. (2019). Comparison of the accuracy of human readers versus machine-learning algorithms for pigmented skin lesion classification: an open, web-based, international diagnostic study. The Lancet Oncology, 20(7), 938–947. DOI: 10.1016/S1470-2045(19)30333-X

[7] Jeong, H. K., Lee, J. H., Kim, J., & Kim, S. (2022). Deep learning in dermatology: a systematic re vie w of current applications and limitations. JID Innovations, (systematic review). (PMC link)

[8] Combalia, M., Codella, N., Rotemberg, V., et al. (2022). Validation of artificial intelligence prediction models for skin cancer diagnosis using dermoscopy images: the 2019 ISIC challenge results. The Lancet Digital Health (validation study). DOI: 10.1016/S2589- 7500(22)00021-8.

[9] Codella, N., Rotemberg, V., Tschandl, P., et al. (2018). Skin Lesion Analysis Toward Melanoma Detection: A Challenge at the 2017 ISIC Grand Challenge. IEEE Journal of Biomedical and Health Informatics / arXiv preprint (ISIC Challenge overview).

[10] Combalia, M., Celebi, M. E., & Tschandl, P. (2020). Analysis of IS IC challenge datasets and benchmarking practices. Computerized Medical Imaging and Graphics (dataset analysis).

[11] Groh, J., & Groh, J. (2020). Fitzpatrick17k: a benchmark dataset for skin tone diversity in dermatology AI. (Dataset description / arXi)

[12] Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions (SHAP). Advances in Neural Information Processing Systems (NeurIPS). DOI/link.

[13] Pacheco, A., & Krohling, R. A. (2021). Multimodal learning for dermatology: combining clinical images andmetadata for improved diagnosis. Scientific Reports / IEEE Access.

[14] Zhu, C.-Y., Yang, S.-C., & Hsieh, C.-H. (2021). A deep learning based framework for diagnosing multiple skin diseases in clinical environment. Sensors, 2021. DOI: 10.3390/sensors20143378

[15] Pacheco, A., & Krohling, R. A. (2021). Attention mechanisms for combining image features and patient metadata in skin disease classification. IEEE Transactions on Medical Imaging (conference/journal article).

[16] Chiou, A. S., et al. (2025). MIDAS—A Multimodal Image Dataset for AI-based Skin Cancer. NEJM AI (dataset & description). DOI/link: ai.nejm.org/… (2025 dataset).

[17] Tschandl, P., et al. (2019). HAM 10000: A large collection of multi -source dermatoscopic images.

[18] Winkler, J. K., et al. (2019). Association of s martphone and clinical photography in dermatology datasets. JAMA Dermatology (mobile/telederm dataset studies).
[19] Yuan, Y., et al. (2017). Automatic skin lesion segmentation using fully convolutional networks with Jaccard distance. IEEE Transactions on Medical Imaging. DOI: 10.1109/TMI.2017.xxx.
[20] Bi, L., Kim, J., Ahn, E., & Feng, N. (2018). GAN-enhanced lesion segmentation for dermoscopic images. Computerized Medical Imaging and Graphics.
[21] Li, Y., et al. (2019). Boundary-aware networks for accurate lesion segmentation. MICCAI / IEEE proceedings.
[22] Adamson, A. S., & Smith, A. (2018). Machine learning and health care disparities in dermatology: Illustrati ve examples and mitigation strategies. JAMA Dermatology / Nature Medicine commentary.
[23] Daneshjou, R., et al. (2022). Fairness evaluation for dermatology AI: A dataset and benchmarking study.Science Translational Medicine / Nature Medicine commentary.
[24] Celebi, M . E., Iyatomi, H., Schaefer, G., & Stoecker, W. V. (2015). Lesion preprocessing techniques for dermoscopy images. Dermatology Practical & Conceptual.
[25] Xie, F., et al. (2020). Deep active contours for robust skin lesion segmentation. IEEE Transactions on Image Processing.
[26] ISIC Archive. International Skin Imaging Collaboration (ISIC) Challenge datasets (2016– 2023). (Dataset portal) — https://www.isic-archive.com.
[27] Groh, J., et al. (2020). Fitzpatrick17k: A benchmark for assessing skin tone bias in dermatology AI. (Dataset paper / arXiv).
[28] Wang, S., et al. (2021). Assessing skin tone representation in dermatology datasets and models. npj Digital Medicine (fairness analysis).
[29] Tschandl, P., et al. (2020). Human–computer collaboration for skin cancer recognition: Steps toward equitable AI. Nature Medicine commentary.
[30] Phillips, M., et al. (2019). Clinical trials and regulatory considerations for diagnostic dermatology AI. NPJ Digital Medicine / The Lancet Digital Health (clinical validation guidelines).
[31] Garg, A. X., et al. (2019). Impact of clinical decision support systems on practitioner performance: Meta-analysis. JAMA / Systematic review (relevance to AI adoption).
[32] Xie, Y., et al. (2021). Vision transformers for skin lesion classification. arXiv preprint / MICCAI.
[33] Karim, R., et al. (2022). Attention U-Net and transformer hybrids for lesion segmentation. IEEE Transactions on Medical Imaging.
[34] LesionNet (2023). Transformer + U-Net hybrid for boundary-aware segmentation. Medical Image Analysis.
[35] Wang, Y., et al. (2023). Combining Grad-CAM and SHAP for dermatology model explanations. Medical Image Analysis (XAI application study).
[36] Chanda, S., et al. (2024). Dermatologist-like explainable AI enhances clinical trust in automated skin diagnosis. Nature Communications (XAI + clinical evaluation).
[37] Codella, N., et al. (2018). Skin lesion analysis toward melanoma detection (ISIC 2017): Challenge overvie w and results. IEEE Journal of Biomedical and Health Informatics.
[38] Combalia, M., et al. (2022). Real-world validation of dermoscopy AI models: Lessons from ISIC 2019/2020. The Lancet Digital Health.
[39] Hekler, A., et al. (2019). Designing AI workflows for dermatology clinical practice: human factors and usability. JAMA Dermatology / Human-Computer Interaction studies.
[40] PanDerm (Yan et al., 2025). A multimodal foundation model for clinical dermatology. Nature Medicine large multimodal foundation model).
[41] Selvaraju, R. R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2017). Grad CAM: Visual explanations from deep networks vi a gradient-based localization. Proceedings of the IEEE International Conference on Computer Vision (ICCV) , 2017. DOI: 10.1109/ICCV.2017.74.