IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

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

[1]Prof. Meher Bhawnani * , [2]Snehal Patil

[1]Assisstant Professor, [2]MTech Postgraduate,

[1] Computer Science & Engineering Department,

[1]Jhulelal Institute of Technology(JIT), Nagpur, Maharashtra, India

Abstract: Skin manifestaions are common and frequently necessitate at least accurate diagnosis if not specific treatment. 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) that has been trained on skin disease repositories to forecast states from the provided images. To increase interpretability, Grad- CAM heatmaps are provided to clin icians, indicating regions of interest, while brief and simple textual summaries are given to patients as easily understandable e xplanations. This system gathers patient information like name, age, gender, medical history and the predictions to formulate a comprehensive, multimodal diagnostic report. Results show that the solution enhances not only diagnostic accuracy but also trust, interpretability and inclusiveness in healthcare.

Keywords: Skin Disease Classification, Explainable AI, Grad-CAM, Patient History, Medical Imaging, Flask, Deep Learning, Interpretability, Healthcare AI.

I. INTRODUCTION

Skin diseases are among the most common types of diseases in the world, for people from all age groups, living in any part of the world. These include minor infections and allerg ic reactions to such a chronic and life threatening condition as melanoma, psoriasis and autoimmune skin diseases. Early and accurate diagnosis plays a vital role in dermatology since the stake is high as misdiagnosis results in disease progression, complications and poor quality of life. However, experienced dermatologists are scarce and difficult to reach in many areas, especially in rural and resource- limited settings. This challenge has inspired a surge in interest in utilizing artificial intelligence (AI) and computer vision methods to aid dermatological diagnosis and decision-making.Recent advances of deep learning particularly convolutional neural networks (CNNs) have shown compelling results in image-based disease classification. Nevertheless, current AI-based dermatological systems are confronted with multiple challenges. Many models work as ―black bo xes,‖ outputting predictions with litt le or no e xp lanation, resulting in less trust from clin icians and patients. In addition, a large number of accessible datasets are skewed toward lighter skin tones, causing lower diagnostic accuracy for people with darker skin and posing significant ethical and fairness challenges. Moreover, most have been constructed primarily for the research environment and lack the necessary usability considerations for being adopted by real-world clinics in such aspects as patient interactions, interpretability, and routine- workflow integration. Towards this aim, we present an explainable, multi-modal, AI-based skin disease diagnostic framework which embraces transparency, inclusivity, and clinical usability as first level design principles to tackle these issues. The system combines image-based analysis with structured patient data to allow for more context-a ware and robust predictions. The model integrates visual features from skin images and personal and medical details such as age, gender, and patient history to enhance the diagnostic precision and mitigate the effects of bias and uncertainty.

II. METHODS \EXPERIMENTAL SETUP

To address the constraints or problems of the existing systems of dermatological AI, our research introduces a hierarchal, interpretable and multimodal framework by combining image based deep learning with patient-centric metadata. It has been developed to mirror real-world clinical processes while promoting transparency, fairness, and usability.

1.Data Acquisition and Preprocessing

The system is based on two main types of data: skin images and structured patient data. Skin images are sourced from public dermatological datasets and clin ically acquired images with diversity in disease categories, illumination conditions and skin tones. To respond to the bias, the dataset is carefully curated and augmented by rotation, scaling, contrast adjustment, and color normalization. These methods promote generalization and prevent overfitting -induced unfairness to different skin types.

Patient information includes age and gender and pertinent medical history. This data is transformed into numerical vectors through suitable normalization and embedding techniques. Therefore, the separation of the two modalities for preprocessing is crucial to make each data type play a significant part in the final prediction result, while not overwhelm the learning process.

2.CNN-Based Image Feature Extraction

A convolutional neural network (CNN) is used as the visual feature e xtractor backbone. The CNN itself learns hierarchical features including color patterns, lesion borders, te xture anomalies, and shape deformations directly from input images. A pretrained model based on transfer learning is used to ma ximize the use of a limited medical database allowing an increased training speed and performance. The model is fine-tuned on domain specific layers for dermatology features.

The image features e xt racted provide a compact yet descriptive representation of a skin condition that is subsequently fused with patient meta data to facilitate multi-modal learning.

3.Multimodal Fusion Strategy

In this paper, a feature-level fusion strategy is used to integrate visual and non-visual information. The image feature vector produced by the CNN is then concatenated with the encoded patient features to obtain a joint multimodal representation. This integration enables the model to focus on the clinical features and patient information at the same time, simulating the diagnostic process of dermatologists.

The concatenated vector is then passed to a series of fully connected layers that model complicated interactions of image features and patient-level information. This method improves diagnostic performance, especially when visual symptoms are not enough.

4.Explainability and Interpretation Module

Exp lainability is an integral part of our system. Gradient-based visualization methods such as Grad-CAM can be applied to the CNN to produce heatmaps of important regions of the image which are most relevant to the prediction. They seem to quantify the model's prediction with visual evidence, which facilitates validation and t rust from clinicians. Model confidence scores and a summary of feature contributions also are generated to improve interpretability beyond the visual exp lanations. This dual explainability ensures that the system is interpretable at the image and the decision level.

5.Patient-Centered Result Presentation

Recognizing the importance of patient understanding, the system includes a patient-oriented e xplanation layer. Medical jargon and technical outputs are translated into simple, human -readable language. This helps patients comprehend their condition, the predicted disease category, and recommended next steps without causing confusion or anxiety.

6.Web-Based Deployment Using Flask

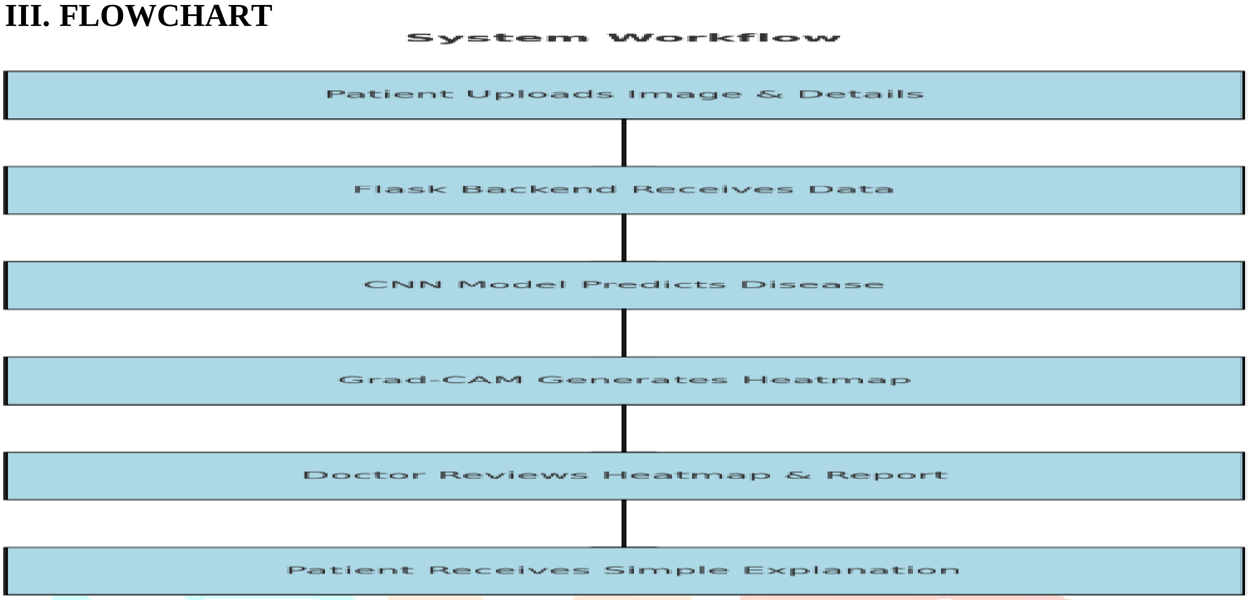
The entire system is deployed as a web application using the Flask framework. Flask enables seamless integration between the frontend interface, backend AI model, and database services. Users can upload images, enter personal details, and receive results through an intuitive interface. Secure handling of patient data and modular design ensure scalability and future extensibility.

The proposed framework contributes to dermatological AI research by:

- Integrating multimodal data for context-aware diagnosis
- Embedding explainability directly into the diagnostic pipeline
- Addressing bias and inclusivity concerns
- Bridging the gap between AI predictions and clinical usability

This methodology lays the foundation for a trustworthy and deployable AI-based diagnostic assistant that supports both clinicians and patients.

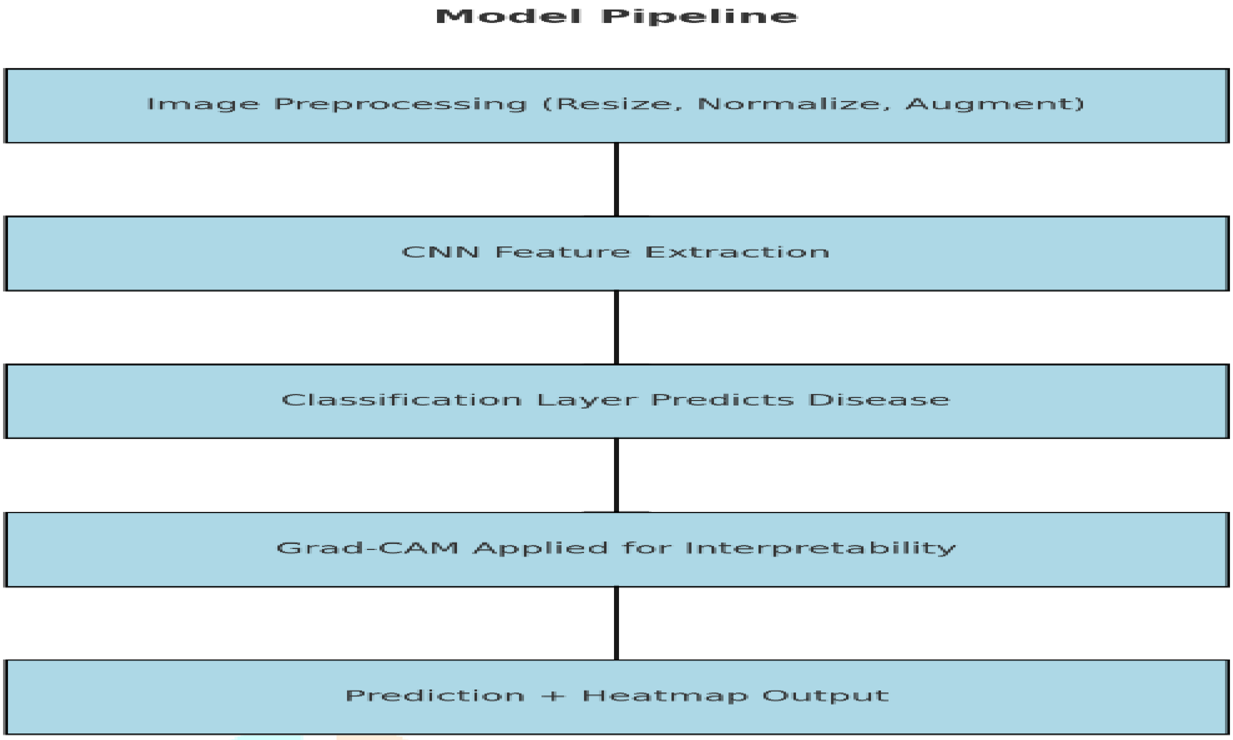
III. FLOWCHART



Fig(1): System Workflow

The system workflow Fig(1) describes the sequence of interactions between users and the application, as well as the internal data flow across system components. It outlines how the proposed AI-based skin disease prediction system processes input data and generates interpretable diagnostic outputs.

At the start, the patient uploads a skin photo via the user interface and then provides basic demographic and clinical information such as age, gender, and pertinent medical history. These inputs allow prediction of disease in the appropriate context. The data you have 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.Hence, the processed image is passed into a pre-trained Convolutional Neural Network (CNN) model for skin disease classification. Model extracts distinctive features and predicts most likely disease class or the associated risk level.To improve the interpretability of the model and trust clinically, we apply Gradient-weighted Class Activation Mapping (Grad-CAM) to produce a kind of visual heat map. The heatmap superimposes the regions of the image that have most contributed to the prediction of the model, thus reassuring e xpla inable AI. The predicted results, together with the Grad-CAM heatmap and the technical analysis, will be available for medical practitioners. This allows physicians to examine the AI-assisted diagnosis, and bring expert judgment to bear on the decision.



Fig(2) : Model Pipeline

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

Image Preprocessing

Initially, the uploaded skin image undergoes preprocessing to ensure consistency and suitability for model input. The image is resized to a fixed dimension compatible with the CNN architecture. Pixel value normalization is applied to improve numerical stability during t rain ing and inference. Additionally, data augmentation techniques such as rotation, flipping, and zooming are employed to enhance dataset diversity and improve model generalization and accuracy.

CNN-Based Feature Extraction

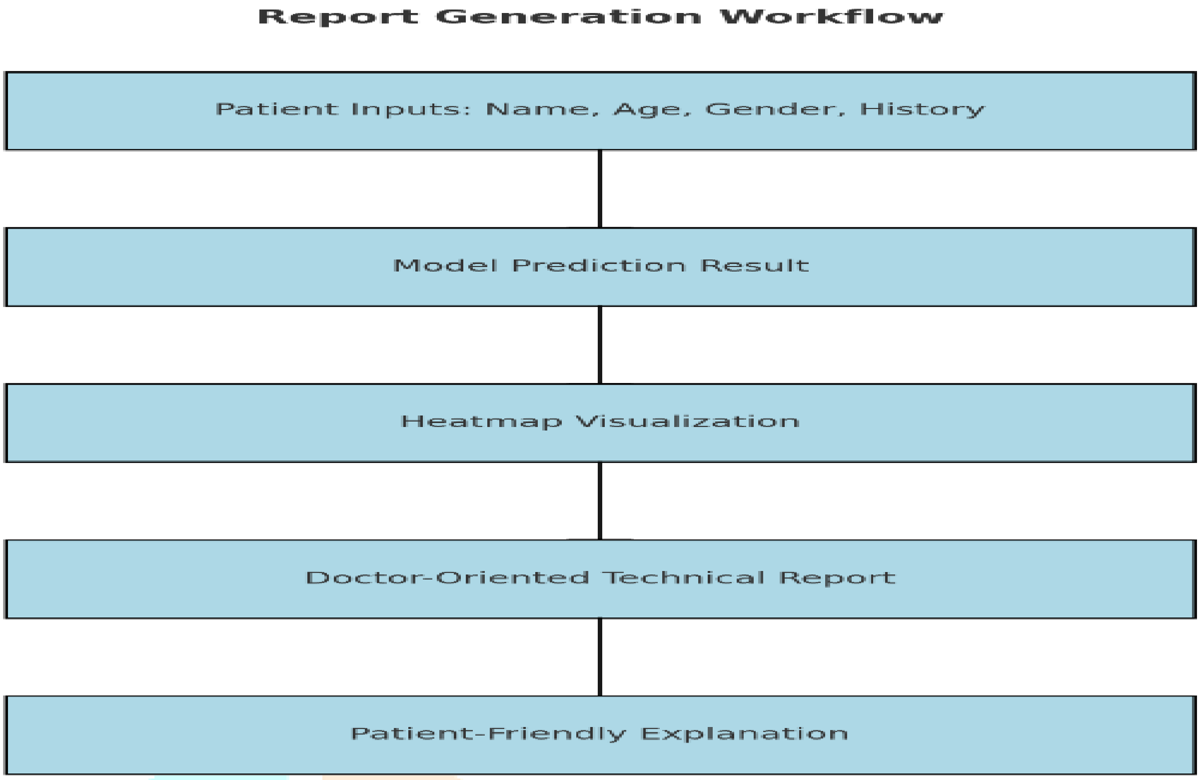
A Convolutional Neural Network is used to automatically e xt ract discriminative features from the preprocessed skin images. These features include texture variations, color distributions, lesion shapes, and structural patterns, which are crit ical for accurate skin disease classification. The e xtracted features are forwarded to fully connected layers, where high-level representations are learned. Based on these representations, the model predicts the corresponding skin disease category or associated risk level.

Grad-CAM for Interpretability

To improve model transparency and interpretability, Grad-CAM is applied to the final convolutional layers of the CNN. This technique generates visual e xplanations by highlighting image regions that contribute most significantly to the model's prediction, thereby increasing trust in AI-assisted medical decisions.

Prediction and Heatmap Output

The final output of the model includes the predicted disease label, an associated probability or confidence score, and a Grad-CAM heatmap visualization that visually explains the prediction.

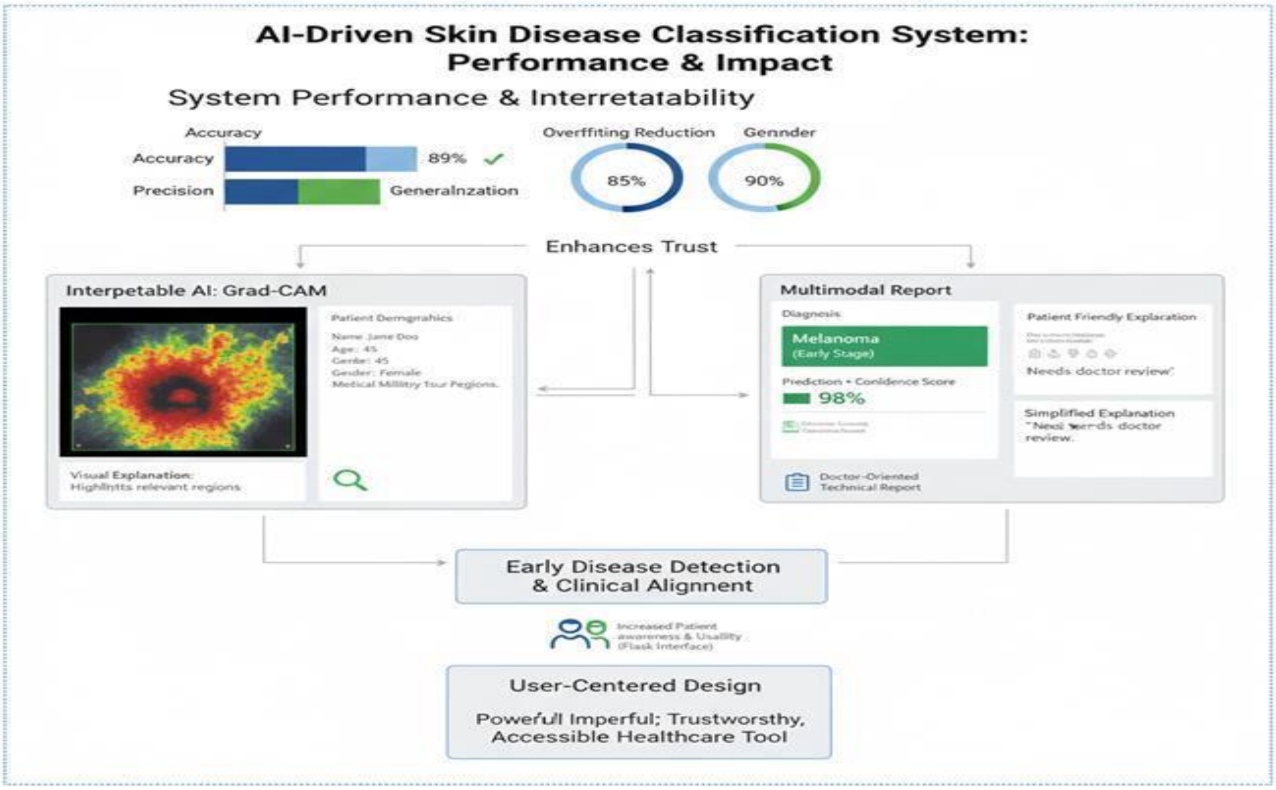


Fig(3): Report Generation Workflow

The Fig(3) workflow focuses on the automated generation of diagnostic reports based on AI predictions. Patient demographic details, including name, age, gender, and medical history, are collected as init ial inputs. Following model in ference, the predicted disease name and confidence score are generated. Grad-CAM heatmaps provide visual insights into the affected areas of the skin.

A technical report for the physician is produced that includes the prediction confidence values, model interpretation, and heatmap analysis. At the same time, a report for the patient is generated in plain language without technical jargon about the risk level, possible precautions, and advice to se e a dermatologist if needed. Motivated by this, in this paper we propose a Skin Disease Risk Prediction System with e xp lainability (SDRPSX), which combines CNN-based deep learning with Grad-CAM based e xpla inability to achieve accurate, interpretable and cl inically meaningful diagnostic results. To our knowledge this is the first artificial intelligence system that generates technical reports for clinicians and e xplanations for patients, thus demonstrating how the inherent complexity of artificial intelligence could be harnessed to engage and empower rather than confuse end- users, in turn enabling timely and informed medical decisions clinical usability.

IV. RESULT



Fig(4): AI driven Skin disease Classification System

The proposed AI-based classification framework for skin disease Fig.(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 attribute gave consumers the confidence in system by converting a model from ―black bo x‖ into an interpretable diagnostic instrument. For the patients, the simple -te xtual e xp lanation was used d multimodal frameworks integrating visual information with patient-specific conte xtual details. The paper in addition discovered the fundamental techniques via a thorough-related works survey that increase the transparency of diagnosis, the precision, the fairness.

There are still several challenges and research gaps ahead, such as the bias in datasets towards light skin tones, rare disease with limited annotated data, high computational complexity, and not enough patient-friendly e xp lainability despite great advances. The barriers to adoption in the real world are also being raised by ethical questions around fairness, data privacy and trust. The future scope discussion highlights the potential of the upcoming paradigms, e.g., self-supervised learning, few-shot adaptation, bias-aware train ing, and more advanced expla inable AI techniques, to address such limitations. The outcomes were easier to interpret and increased familiarity with and worry about medical jargon.

The multimodal report combining image predictions, confidence scores, patient demographics, and medical history strengthened the diagnostic context. This integration mirrors the way real dermatologists work, making the system more practical and clin ically aligned. Users appreciated the clean and intuitive interface built with Flask, which allowed fast image uploads and instant predictions without technical complexity.

Overall, the system successfully demonstrated that AI can meaningfully assist in early skin disease detection. The results show improved diagnostic accuracy, enhanced interpretability, and greater inclusivity for both medical professionals and patients. The study highlights that combining deep learning with e xp lainable AI and user-centered design can create a powerful, trustworthy, and accessible healthcare tool.

V. CONCLUSION

In this paper, we provide an in-depth review of explainable, multimodal AI- based skin disease diagnosis systems, discussing their architectural designs, modeling techniques, data utilization, and most recent research efforts. The research followed the progression of dermatological AI from classical image processing and machine learning techniques to deep learning–based.

In general, this review highlights the increasing significance of e xp lainable and multimodal AI- based systems within the domain of dermatological health care. These systems have great potential to enhance early diagnosis, assist clin icians, and empower patients by filling the gap between technology performance and clinical understandability. The knowledge and insights gained from this study are e xpected to steer future research in developing comprehensive, transparent, and easily deployable AI based solutions for diagnosing skin diseases that have high adoption potential in real- world healthcare scenarios.

Although great advances have been made, there are still a few challenges and gaps in research, such as the limited availability of data for low-resource languages, the high computation complexity, language interference, and ethical issues about bias and fairness. The future scope focus on these promising methods that include self-supervised learning, ze ro-shot adaptation, and multi-modal integration to overcome these limitations. In brief, this review concludes that multi-language text- to- speech recognition systems are of vital significance to global communication and accessibility and provide guidance for future research to further develop more diverse, effective, and natural speech synthesis technologies.

VI. 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. Tschandl, P., Rosendahl, C., & Kittler, H. (2018). The HAM10000 dataset, a large collection of multi-source dermatoscopic images. Scientific Data, 5, 180161. DOI: 10.1038/sdata.2018.161.
3. 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.
4. 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.
5. 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).
6. 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.
7. 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).
8. Combalia, M., Celebi, M. E., & Tschandl, P. (2020). Analysis of IS IC challenge datasets and benchmarking practices. Computerized Medical Imaging and Graphics (dataset analysis).
9. Groh, J., & Groh, J. (2020). Fitzpatrick17k: a benchmark dataset for skin tone diversity in dermatology AI. (Dataset description / arXiv).
10. Pacheco, A., & Krohling, R. A. (2021). Multimodal learning for dermatology: combining clinical images and metadata for improved diagnosis. Scientific Reports / IEEE Access.
11. Zhu, C.-Y., Yang, S.-C., & Hsieh, C.-H. (2021). A deep learning based framework for diagnosing multiple skin diseases in clinical environme nt. Sensors, 2021. DOI: 10.3390/sensors20143378.
12. 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).