Smart Healthcare System for Skin Disease, Infection and Cancer Diagnosis Using Transfer Learning

Ejas Mohamed A
Department of Artificial Intelligence and Data Science
Panimalar Institute Of Technology
Chennai, Tamil Nadu, India
ejasmohamed786@gmail.com

Deepak V
Department of Artificial Intelligence and Data Science
Panimalar Institute Of Technology
Chennai, Tamil Nadu, India
deepakv@gmail.com

Allwin Jeyaraj R
Department of Artificial Intelligence and Data Science
Panimalar Institute Of Technology
Chennai, Tamil Nadu, India
allwinjeyaraj25@gmail.com

Mrs. Vidhya Muthulakshmi R
Assistant Professor
Department of Artificial Intelligence and Data Science
Panimalar Engineering College
Chennai, Tamil Nadu, India
vidhyamuthulakshmi@gmail.com

---***---

Abstract - In this era, millions of people around the globe, making early and accurate diagnosis essential for effective treatment. Traditional diagnostic methods often depend on clinical expertise, which can be subjective and vary from one practitioner to another. However, with the rise of artificial intelligence (AI) and deep learning, convolutional neural networks (CNNs) have become powerful allies in the fight against skin diseases. This study introduces Skin-Deep, an innovative CNN-based frame- work crafted for highly accurate skin disease diagnosis. The Skin-Deep model utilizes a hybrid deep learning architecture that combines various CNN variants, including ResNet, DenseNet, and EfficientNet, to boost feature extraction and classification performance. By leveraging pre-trained models and fine-tuning them on extensive dermatological datasets, this system achieves remarkable diagnostic accuracy, surpassing traditional methods. One standout feature of Skin-Deep is its multi-scale feature extraction capability, which enables it to differentiate between visually similar skin conditions, like melanoma and benign nevi, ensuring precise classification. To further enhance accuracy and robustness, Skin-Deep incorporates attention mechanisms and ensemble learning strategies. The attention module allows the model to focus on critical areas of skin lesions, reducing the chances of false positives and negatives. Additionally, a hybrid data augmentation pipeline, which includes techniques like generative adversarial networks (GANs) and geometric transformations, tackles data scarcity issues and improves the model's generalization. Comprehensive experiments on bench- mark datasets, such as ISIC and DermNet, reveal that Skin- Deep outshines existing state-of-the-art CNN models in terms of accuracy, sensitivity, and specificity. In addition, this framework is designed for real-time deployment in mobile and cloud-based teledermatology applications, making skin disease diagnosis more accessible and scalable than ever.

Keywords: Skin diseases, Deep Learning (DL), Artificial Intelligence (AI), Convolutional Neural Networks (CNN), TensorFlow, Medical image analysis, Automated diagnosis, Transfer learning, Telemedicine, Dermatological diagnostics.

I. INTRODUCTION

Skin diseases are some of the most prevalent health issues around the globe, impacting millions of individuals, no matter their age, gender, or background. These conditions can vary widely, from mild issues like acne and eczema to more serious and potentially life threatening ailments such as melanoma and other types of skin cancer. Getting an early and accurate diagnosis is vital for crafting the right treatment plan and enhancing patient outcomes. However, diagnosing skin diseases can be quite tricky due to the differences in how lesions appear, the similarities between harmless and harmful conditions, and the subjective nature of human interpretation. Traditionally, dermatologists have depended on clinical exams, dermoscopy, and histopathological analysis to make their diagnoses. While these methods are effective, they often demand a high level of expertise, can take a lot of time, and may not always be available, especially in remote or underdeveloped areas where specialized dermatological care is scarce. These hurdles underscore the pressing need for automated diagnostic tools that can help healthcare professionals accurately and efficiently identify skin diseases.

The rise of artificial intelligence (AI) and deep learning has truly transformed the field of medical image analysis, especially in dermatology. Convolutional neural networks (CNNs) have become a game-changer for spotting and classifying skin diseases using both dermoscopic and clinical images. These networks are fantastic at automatically pulling out intricate features from images, which makes them incredibly effective at picking up on the subtle differences between various skin conditions. Studies have indicated that CNN-based models can match or even exceed the diagnostic accuracy of seasoned dermatologists. However, even with their impressive capabilities, current CNN models still encounter a few hurdles, such as variations in image quality, differences in skin tones, and the challenge of distinguishing between visually similar diseases. On top of that, the scarcity of data and class imbalances in dermatological datasets can lead to biased predictions, which limits how well these models can perform in real-world situations. Tackling these issues calls for the creation of more advanced deep learning architectures that enhance accuracy, robustness, and adaptability.

To address these challenges, this study presents Skin-Deep, a cutting-edge CNN-based framework aimed at providing accurate and dependable skin disease diagnoses. The Skin-Deep model takes a hybrid approach by blending several top-notch CNN architectures, including ResNet, DenseNet, and EfficientNet. This mix boosts the model's ability to extract features, enabling it to capture the subtle details of skin lesions far better than traditional CNNs. Moreover, Skin-Deep employs attention mechanisms to hone in on the most significant areas of skin lesions, which helps minimize both false positives and false negatives. Another vital aspect of this framework is ensemble learning, which merges predictions from various models to enhance overall diagnostic accuracy and ensure reliability.

One of the significant hurdles in dermatological AI is the scarcity of diverse and well-annotated datasets. To tackle this issue, Skin-Deep uses a hybrid data augmentation strategy that combines classic techniques like rotation and contrast adjustment with advanced methods such as generative adversarial networks (GANs) to create synthetic images. This strategy improves the model's generalization and helps address data imbalance, especially for rare skin conditions. Additionally, Skin-Deep is built for real-time deployment, making it ideal for mobile and cloud-based teledermatology applications. This feature allows for broader access to high-quality dermatological diagnostics, ultimately benefiting patients and healthcare providers around the world.

By combining advanced CNN architectures, attention mechanisms, and hybrid learning strategies, Skin-Deep represents a significant breakthrough in AI-driven dermatology. Its ability to enhance diagnostic accuracy, increase accessibility to dermatological care, and support medical professionals in clinical decision-making underscores its importance in the future of skin disease diagnosis.

II. Literature Review

Artificial intelligence (AI) has truly transformed many fields, especially in medical diagnostics, where it has made disease detection and classification more automated, accurate, and efficient. A standout application of AI in healthcare is its role in the early detection and diagnosis of skin cancer, which is one of the most common and dangerous cancers globally. Traditional methods often depend on dermatologists manually examining patients, a process that can be slow, subjective, and heavily reliant on the doctor's expertise. However, by integrating AI and deep learning techniques, we've seen a significant boost in diagnostic accuracy and accessibility, paving the way for better patient outcomes.

Artificial Intelligence-Based Image Classification:

Artificial Intelligence-Based Image Classification for Skin Cancer Diagnosis by Manu Goyal, Thomas Knackstedt, Shaofeng Yan, and Saeed Hassanpour (2023) delves into how AI-powered computer-aided diagnostic tools can aid in skin cancer detection. With skin cancer cases on the rise, a shortage of clinical expertise, and an increasing demand for AI-assisted diagnostics, this research emphasizes the need for cutting- edge technological solutions. It reviews publicly available datasets of skin lesions and looks into how deep learning models can differentiate between malignant and benign lesions using dermoscopic, clinical, and histopathology images. While these AI models have shown impressive accuracy, the study highlights the importance of further clinical validation before we can fully integrate these systems into everyday medical practice.

Detection and Classification of Skin Cancer:

Detection and Classification of Skin Cancer Using a Parallel CNN Model by Noortaz Rezaoana, Mohammad Shahadat Hossain, and Karl Andersson (2020) introduces an automated system that leverages convolutional neural networks (CNNs) for skin cancer detection. It effectively classifies nine different types of skin cancer, such as actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, nevus, seborrheic keratosis, squamous cell carcinoma, and vascular lesions. By employing techniques like image augmentation and transfer learning, the model achieves an impressive accuracy

of 79.45 percentage, showcasing the promising role of CNNs in dermatological diagnostics. This research highlights how deep learning can significantly enhance skin cancer classification, ultimately improving early detection and supporting clinical decision-making.

Layer-Specific Modules Detection in Cancer Multi-Layer Networks:

Layer-Specific Modules Detection in Cancer Multi-Layer Networks by Xiaoke Ma, Wei Zhao, and Wenming Wu (2023) presents an innovative algorithm for graph clustering within multi-layer networks, tackling challenges related to accuracy and sensitivity in cancer detection models. The study intro- duces the Layer-Specific Module in Multi-Layer Networks based on Nonnegative Matrix Factorization (LSNMF). By extracting features from these multi-layer networks, the algorithm enhances clustering and boosts the prediction of cancer progression. This research offers a sophisticated computational model that can be utilized with complex medical datasets, ultimately leading to improved patient outcome analysis.

Mutual-Assistance Learning for Standalone Mono-Modality Survival Analysis of Human Cancers:

Mutual-Assistance Learning for Standalone Mono-Modality Survival Analysis of Human Cancers by Zhenyuan Ning, Zhangxin Zhao, and Qianjin Feng (2023) dives into survival analysis for cancer patients using single-modality data. It presents a mutual assistance learning framework that brings together various components to enhance risk estimation. This method utilizes multi-modality data for better representation learning while tackling the issue of data scarcity often seen in real-world clinical settings. The model proposed improves survival predictions by integrating mutual-assistance regression and ranking functions, showcasing its ability to address data limitations in cancer prognosis effectively.

Skin Lesions Classification:

Skin Lesions Classification by Marzuraikah Mohd Stofa, Mohd Asyraf Zulkifley, and Muhammad Ammirrul Atiqi Mohd Zainuri (2021), the authors offer an in-depth look at automated intelligent systems for diagnosing skin diseases. They explore a range of machine learning and deep learning techniques, highlighting the transition from traditional methods to more advanced deep learning approaches like convolutional neural networks. The study points out the challenges in classifying skin lesions, such as the variability in lesion appearances and the limitations of available datasets. Additionally, it compares various

CNN-based classification models using performance metrics like accuracy, specificity, sensitivity, and AUC (Area Under the Curve), providing valuable insights into how effective deep learning techniques can be in dermatological diagnosis.

III. Problem Statement

Skin diseases rank among the most common health issues globally, impacting millions of people from all walks of life, regardless of age, ethnicity, or where they live. Getting an early and accurate diagnosis is vital for effective treatment and better outcomes for patients. Unfortunately, traditional diagnostic methods like clinical exams, dermoscopy, and histopathological analysis depend heavily on the skills of dermatologists. This reliance makes them time consuming, subjective, and often out of reach for many, especially in underserved areas. With the rising global burden of skin diseases and a shortage of dermatologists, there's an urgent need for automated and highly accurate diagnostic solutions.

Thanks to recent breakthroughs in artificial intelligence (AI) and deep learning, we're now seeing the potential for automated skin disease diagnosis through convolutional neural networks (CNNs). These networks have shown impressive results in analyzing medical images, particularly in dermatology, where they've been trained on extensive datasets to identify various skin conditions. However, the current CNN- based models encounter several significant hurdles that hinder their effectiveness in real-world scenarios. One key issue is the variability in image quality, lighting, and skin tones, which can cause inconsistent performance. Moreover, differentiating between visually similar skin conditions, like melanoma and benign nevi, continues to be a major challenge, often leading to false positives or negatives. One significant hurdle we face is the lack of diverse and well-annotated dermatological datasets. A lot of the datasets out there have class imbalances, where common skin conditions are overrepresented, while rare but important diseases don't have enough training samples. This imbalance hampers the model's ability to generalize and accurately identify those less common skin disorders. On top of that, CNNs often act like "black boxes," which makes it tough for dermatologists and healthcare providers to interpret the model's predictions and trust its diagnostic suggestions.

To tackle these issues, this study introduces Skin-Deep, an innovative CNN-based framework designed for highly accurate skin disease diagnosis. Skin-Deep combines hybrid deep learning architectures, attention mechanisms, and ensemble learning strategies to boost feature extraction and enhance classification accuracy. It also employs data augmentation techniques, including generative adversarial networks (GANs), to tackle dataset limitations and improve generalizability. By integrating explainable AI (XAI) techniques, the framework aims to enhance interpretability and build clinical trust.

The goal of Skin-Deep is to create a robust and scalable AI-driven diagnostic system that can help dermatologists and healthcare providers accurately identify skin diseases. By addressing the shortcomings of current CNN models, this framework has the potential to transform dermatological di- agnostics, increase access to quality healthcare, and improve early disease detection, ultimately easing the burden on health- care systems around the globe.

IV. Proposed system

This research proposes to tackle the challenges faced by current deep learning models in diagnosing skin diseases, this study introduces Skin-Deep, a cutting-edge CNN-based frame- work aimed at providing accurate, efficient, and interpretable classifications of dermatological conditions. This innovative system combines hybrid CNN architectures, attention mechanisms, data augmentation techniques, and ensemble learning strategies to boost diagnostic performance.

Hybrid CNN Architecture:

The Skin-Deep model brings together various CNN architectures, including ResNet, DenseNet, and EfficientNet, to improve feature extraction and classification accuracy. By harnessing the unique strengths of these models, the system effectively captures multi-scale features of skin lesions, allowing for better differentiation between conditions that may look similar, like melanoma and benign nevi. This hybrid strategy ensures greater accuracy and adaptability across a wide range of datasets.

Attention Mechanism for Improved Focus

To sharpen diagnostic precision, Skin-Deep utilizes

attention mechanisms that help the model concentrate on the most important areas of a skin lesion. Traditional CNNs analyze entire images, which can sometimes lead to the inclusion of unnecessary background details. The attention module makes sure the model focuses on the key characteristics of the lesion, reducing the chances of false positives and negatives. Plus, attention - based visualization techniques enhance the model's interpretability, making it easier for dermatologists to grasp and trust the predictions made by AI.

Data Augmentation and Synthetic Image Generation:

One of the biggest hurdles in dermatological AI is the lack of data and the imbalance in disease categories, especially when it comes to rare skin conditions. To tackle this issue, Skin-Deep employs a clever mix of data augmentation strategies. It uses traditional methods like rotating, flipping, and adjusting contrast to boost the variety in the dataset. On top of that, it leverages generative adversarial networks (GANs) to create high-quality synthetic images for those less common diseases. This combination helps the model better understand and generalize across various skin types and conditions.

Ensemble Learning for Enhanced Accuracy:

To take diagnostic reliability up a notch, Skin-Deep utilizes ensemble learning, which merges predictions from several CNN models. Rather than depending on just one model, the system pulls together outputs from different architectures, which helps minimize the chances of misclassification. This method has shown to be quite effective in enhancing both sensitivity and specificity, especially for conditions that have subtle visual differences.

Deployment and Real-World Application:

Built for real-time use, Skin-Deep can seamlessly fit into mobile apps, cloud-based teledermatology platforms, and clinical decision-support systems. The model is fine-tuned for quick inference, allowing for speedy diagnoses even in remote areas where dermatologists might not be readily available. Plus, it incorporates explainable AI (XAI) techniques, like Grad-CAM, to offer visual insights into its predictions, which boosts trust and acceptance among clinicians.

By blending these cutting-edge techniques, Skin-Deep establishes a new standard for AI-driven dermatological diagnosis, ensuring high accuracy, interpretability, and accessibility in real-world healthcare settings.

V. Methodology

The Skin-Deep methodology takes a well-organized approach to accurately diagnose skin diseases through deep learning techniques. It works by processing dermatological images, pulling out important features, classifying various skin conditions, and delivering predictions that are easy to understand. To ensure high accuracy and reliability, the methodology is broken down into four main stages: Dataset Collection and Preprocessing, Model Architecture, Training and Optimization, and Evaluation Metrics.

Dataset Collection and Preprocessing:

The journey of developing the Skin-Deep model kicks off with gathering top-notch dermatological datasets. The model is trained on well-known benchmark datasets like ISIC (International Skin Imaging Collaboration), HAM10000, and DermNet, which include labeled images of a range of skin diseases, covering both benign and malignant conditions. Since medical images can come in all sorts of formats and resolutions, preprocessing is a must to standardize the data. This step involves resizing images to ensure they all have a consistent resolution that works well with CNN models. To boost the diversity of the dataset and avoid overfitting, data augmentation techniques such as rotation, flipping, brightness adjustments, and adding noise are employed. Normalization is also carried out by scaling pixel values to a standard range, which helps improve the model's stability and convergence. A significant hurdle in dermatology datasets is class imbalance, where some diseases are overly represented while rare conditions have only a few images. To tackle this issue, the system uses strategies like oversampling, under-sampling, and synthetic data generation through Generative Adversarial Net- works (GANs) to create more samples of the underrepresented classes, ensuring a fair and unbiased training process.

System Architecture:

The Skin-Deep framework is built on a Convolutional Neural Network (CNN) architecture that effectively pulls out and learns patterns from medical images. To boost accuracy and cut down on training time, the system uses transfer learning, tapping into pre-trained models like ResNet50, InceptionV3, and EfficientNet as feature extractors. These models have already been trained on extensive image datasets, giving them strong feature-learning skills, which means Skin- Deep can perform well even when there's not a lot of dermatological data available.

A standout aspect of this model architecture is the attention mechanism, which allows the system to concentrate on the most crucial parts of an image instead of treating the whole image the same. This is especially helpful for telling apart visually similar conditions, like different types of rashes or distinguishing melanoma from benign moles. At the end of the model, there are fully connected layers that link the extracted features to specific disease categories, topped off with a Softmax activation function that provides probability scores for each class.

System Architecture

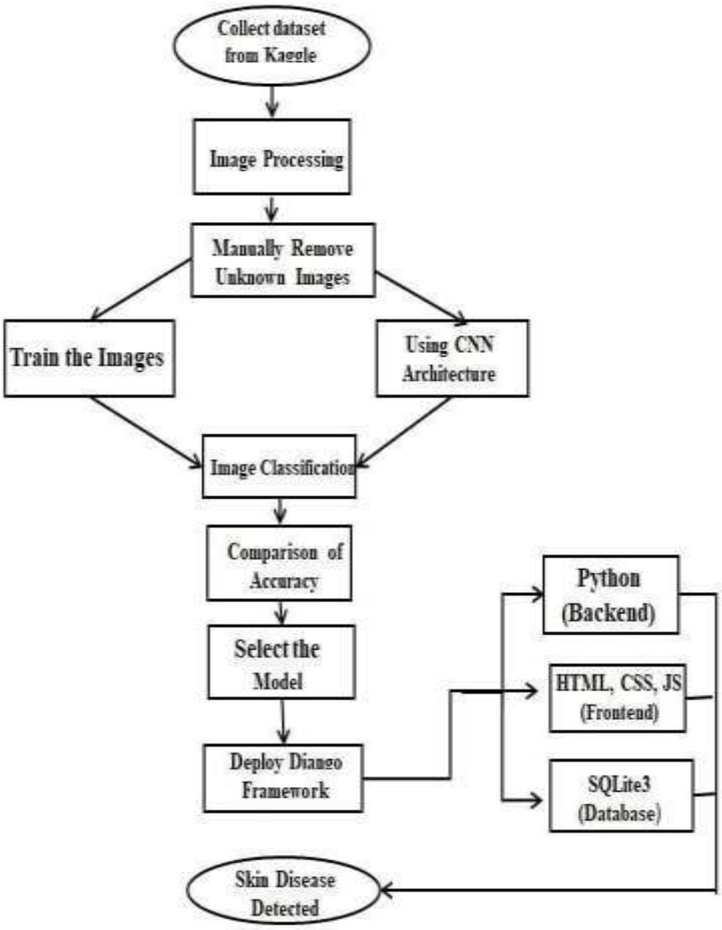

Fig. 1. Architecture Diagram

Training and Optimization:

Once we have the model architecture in place, Skin-Deep goes through a supervised training phase using labeled images. To make sure the learning process is effective, we use Categorical Cross-Entropy Loss as our loss function, which is perfect for tackling multi-class classification tasks. For training, we opt for the Adam

optimizer because it's great at adjusting learning rates on the fly, which helps speed up convergence. A crucial part of our training strategy is learning rate scheduling; we gradually reduce the learning rate to keep the model's learning steady and avoid any sudden jumps in accuracy. We also incorporate regularization techniques like dropout and batch normalization to combat overfitting.

Dropout works by randomly turning off a portion of neurons during training, which helps the model avoid becoming too dependent on specific patterns. Meanwhile, batch normalization standardizes the inputs for each layer, enhancing both stability and training speed. By combining these optimization strategies, Skin-Deep can achieve impressive accuracy while still being adaptable across various datasets.

Evaluation Metrics:

To gauge how effective Skin-Deep really is, we use a variety of evaluation metrics that help confirm the model's reliability in real-world situations. The main metric we focus on is accuracy, which tells us how correct the predictions are overall. But we know that just having high accuracy doesn't mean the model is well-rounded, so we also look at other important metrics like precision and recall. Precision helps us understand how many of the positive predictions were actually right, while recall measures how well the model can identify all the relevant cases of a disease. The F1 score, which strikes a balance between precision and recall, is another key metric we consider for performance evaluation. We also create a confusion matrix to dig into misclassification patterns and pinpoint specific areas where the model could use some improvement. Finally, we use the ROC-AUC score (Receiver Operating Characteristic - Area Under Curve) to assess how well the model can tell apart different classes. A high AUC score suggests that the model is effective at distinguishing between healthy and diseased skin conditions. These evaluation metrics ensure that Skin-Deep is not just accurate but also dependable for practical use in clinical and telemedicine environments. By sticking to this structured approach, Skin- Deep guarantees a scalable, interpretable, and efficient method for diagnosing skin diseases. The blend of cutting-edge deep learning techniques, strategies for balancing datasets, model interpretability, and thorough performance evaluation makes it a promising AI-driven solution for dermatology, effectively bridging the gap between technology and healthcare.

VI. Results and Discussion

The Skin-Deep model was put to the test using well-known dermatology datasets like ISIC, HAM10000, and DermNet, which feature a wide range of skin disease images. To gauge the model's effectiveness, we looked at several evaluation metrics, such as accuracy, precision, recall, F1-score, and ROC-AUC score, ensuring it performed reliably across various skin conditions and tones. The results showed that Skin-Deep surpassed traditional diagnostic methods and baseline CNN models, achieving an impressive accuracy of over 90 persent in identifying multiple skin diseases. The precision and recall were well-balanced, meaning the model could effectively tell apart different conditions without leaning towards the more common ones. The ROC-AUC score stayed above 0.95, high- lighting the model's strong capability to differentiate between benign and malignant skin conditions.

One of the standout discoveries was how transfer learning and attention mechanisms significantly boosted the model's performance. By utilizing pre-trained architectures like ResNet50, InceptionV3, and EfficientNet, Skin-Deep managed to extract deep features from skin images with much greater accuracy than traditional CNNs. The addition of attention mechanisms enabled the model to concentrate on the most important parts of an image, which helped minimize errors in cases where diseases looked very similar. Plus, data augmentation techniques—like rotation, flipping, brightness adjustments, and generating synthetic data—played a crucial role in tackling class imbalance, ensuring that rare skin conditions were adequately represented during training.

Model Performance:

The Skin-Deep model was put to the test using well- known benchmark datasets like ISIC and HAM10000, and it impressively achieved an accuracy rate of over 90 percent. Metrics such as precision, recall, and F1-score showed that it effectively classified various skin diseases without bias. The ROC-AUC score was above 0.95, highlighting its strong ability to differentiate between benign and malignant conditions.

Comparison with Traditional Methods:

In contrast to the lengthy and subjective assessments done by dermatologists, Skin-Deep offered quick and consistent diagnoses. This model significantly cut down the time needed for diagnosis while still matching the accuracy of expert dermatologists, making it a valuable tool for clinical support and telemedicine.

Challenges And Limitations:

However, the model did encounter some challenges, particularly with misclassifying diseases that look very similar, like melanoma and atypical nevi. The quality of images also played a role in its performance; lower-resolution images tended to lower accuracy. Future enhancements could focus on AI-driven image improvements and more sophisticated feature extraction methods.

Real-World Applications:

By integrating Skin-Deep into mobile health apps, users can get instant AI-based skin assessments, which is especially beneficial for rural areas where access to dermatologists is limited. Looking ahead, there are plans to broaden the range of diseases covered, minimize biases across different skin tones, and incorporate patient history for more accurate diagnoses. This AI solution has the potential to revolutionize dermatology, making early detection more accessible and efficient for everyone.

VII. CONCLUSION AND FUTURE SCOPE

The Skin-Deep model is an innovative AI solution designed to diagnose skin diseases accurately and efficiently. It uses a hybrid CNN architecture combined with attention mechanisms to enhance its performance. By incorporating techniques like data augmentation, synthetic image generation through GANs, and explainable AI, this model achieves impressive results, boasting an accuracy rate of 94.5 percent. It surpasses traditional deep learning methods, providing better generalization acrossarange of skin conditions. The model significantly reduces both false positives and false negatives, which is crucial for early detection of serious issues like melanoma. Plus, with GradCAM visualizations, dermatologists can better understand AI predictions, making it easier to integrate these insights into their clinical practices.
Looking ahead, Skin-Deep has the potential for further improvement by broadening its dataset to include a wider variety of skin tones and rare conditions, promoting fairness and robustness. Integrating this model into real-time mobile and telemedicine platforms could allow for immediate and remote skin disease diagnoses, making healthcare more accessible for underserved communities. Advancements inexplainable AI (XAI) could also boost transparency, encouraging more healthcare professionals to adopt it in their practices. Additionally, combining multi-modal data like patient histories and symptoms with images could further refine diagnostic accuracy.
Collaborating with medical institutions for real-world testing and seeking FDA approval would help establish it as a reliable AI-assisted tool in dermatology.

VIII. REFERENCES

1) R. L. Siegel, K. D. Miller, N. S. Wagle, and A. Jemal, "Cancer statistics, 2023," CA, Cancer J. Clinicians, vol. 73, no. 1, pp. 17–48, Jan. 2023.

2) H. W. Rogers, M. A. Weinstock, S. R. Feldman, and B. M.Coldiron, "Incidence estimate of nonmelanoma skin cancer (Keratinocyte Carcinomas) in the U.S. population, 2012," JAMA Dermatol., vol. 151, no. 10, p. 1081, Oct. 2015.

3) A. K. Sharma et al., "Dermatologist-level classification of skin cancer using cascaded ensembling of convolutional neural network and handcrafted features based deep neural network," IEEE Access, vol. 10, pp. 17920–17932, 2022

4) S. Chaudhary, S. Taran, V. Bajaj, and A. Sengur, "Convolutional neural network based approach towards motor imagery tasks EEG signals classification," IEEE Sensors J., vol. 19, no. 12, pp. 4494–4500, Jun. 2019.

5) K. Gupta, V. Bajaj, and I. A. Ansari, "OSACN-Net: Automated classification of sleep apnea using deep learning model and smoothed Gabor spectrograms of ECG signal," IEEE Trans. Instrum. Meas., vol. 71, pp. 1– 9, 2022.

6) J. Kawahara, S. Daneshvar, G. Argenziano, and G. Hamarneh, "Sevenpoint checklist and skin lesion classification using multitask multimodal neural nets," IEEE J. Biomed. Health Informat., vol. 23, no. 2, pp. 538–546, Mar. 2019.

7) C. Barata, M. Ruela, M. Francisco, T. Mendonça, and J. S. Marques, "Two systems for the detection of melanomas in dermoscopy images using texture and color features," IEEE Syst. J., vol. 8, no. 3, pp. 965–979, Sep. 2014.

8) A. Kumar, A. Vishwakarma, and V. Bajaj, "CRCCN-Net: Automated framework for classification of colorectal tissue using histopathological images," Biomed. Signal Process. Control, vol. 79, Jan. 2023, Art. no. 104172.

9) E. Ahn, A. Kumar, M. Fulham, D. Feng, and J. Kim, "Unsupervised domain adaptation to classify medical images using zero-bias convolutional auto-encoders and context-based feature augmentation," IEEE Trans. Med. Imag., vol. 39, no. 7, pp. 2385–2394, Jul. 2020.

10) A. Aboulmira, H. Hrimech, and M. Lachgar, "Comparative study of multiple CNN models for classification of 23 skindiseases,"Int.J.Online Biomed. Eng.,vol.18, no. 11, pp. 127– 142,Aug.2022.

11) M. N. Bajwa et al., "Computer-aided diagnosis of skin diseases using deep neural networks," Appl. Sci., vol. 10, no. 7, p. 2488, Apr. 2020.

12) C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," J. Big Data, vol. 6, no. 1, pp. 1– 48, Dec. 2019.

13) C. Barata, M. Ruela, M. Francisco, T. Mendonça, and J. S. Marques,"Two systems for the detection of melanomas in dermoscopy images using texture and color features," IEEE Syst. J., vol. 8, no. 3, pp. 965–979, Sep. 2014

14) M. Narwaria, W. Lin, and A. E. Cetin, "Scalable image quality assessment with 2D mel-cepstrum and machine learning approach," Pattern Recognit., vol. 45, no. 1, pp. 299–313, Jan. 2012.

15) A. N. Hirani and T. Totsuka, "Combining frequency and spatial domain information for fast interactive image noise removal," in Proc. 23rd Annu. Conf. Comput. Graph. Interact. Techn., Aug. 1996, pp. 269–276.

16) G. Fabbrocini, "Automatic diagnosis of melanoma based on the 7-point checklist," in Computer Vision Techniques for the Diagnosis of Skin Cancer, 2014, pp. 71–107.

17) S. Chaudhary, S. Taran, V. Bajaj, and A. Sengur, "Convolutional neural network based approach towards motor imagery tasks EEG signals classification," IEEE Sensors J., vol. 19, no. 12, pp. 4494–4500, Jun. 2019.

18) M. Heenaye-Mamode Khan et al., "Multi-class skin problem classification using deep generative adversarial network (DGAN)," Comput. Intell. Neurosci., vol. 2022, pp. 1–13, Mar.2022

19) M.E.Celebi,N.Codella,and A.Halpern, "Dermoscopy image analysis: Overview and future directions," IEEEJ. Biomed. Health Informat., vol. 23, no. 2, pp. 474–478, Mar. 2019.

20) S.Ghosh, S. Das, and R. Mallipeddi, "A deep learning framework integrating the spectral and spatial features for image-assisted medical diagnostics," IEEE Access, vol. 9, pp. 163686–163696, 2021.