

## Skanguard-Ai FOR Preliminary Diagnosis OF Dermatological Manifestations

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### ABSTRACT

We introduce an AI-based diagnostic system that supports the initial analysis of dermatological conditions based on clinical skin photos. The algorithm makes a disease prediction and confidence score after processing the input image. A score closer to 1 shows a high level of certainty that it is that type of diagnosis, while lower values tend to indicate more ambiguous classifications. The technology also marks features in vital areas of the image that had the most impact on the model's final class of the image, providing visual interpretability using explainable AI methods.

**Keywords:** Skin Disease Detection, CNN, Image Classification, LIME, Explainable AI, Skincare Recommendations, Deep Learning.

### I. INTRODUCTION

In modern healthcare, dermatological services are important in caring for the skin in all age groups, especially in rural or underserved areas, where there is a real lack of prompt and accurate dermatologic services. Without treatment, dermatological conditions can advance and affect an individual's physical or mental well-being. Such systems are increasingly in demand and utilize different types of complex algorithms, such as CNNs, to monitor skin disease.

Deep learning algorithms are particularly valuable in estimating images in the medical domain. With the rapid advancement in machine learning and its application in dermatology, these models automatically learn visual patterns of different dermatological conditions and provide promisingly accurate predictions. Explainable AI (XAI) techniques like LIME have been proposed to visualize contributing image regions that affect prediction more [8].

Our specific aim of the project is to apply deep learning approaches to process and analyze clinical skin images and offer a clinical diagnosis. It gives a prediction of what disease the microorganism likely belongs to with an associated score for confidence and visual reasoning for why the prediction was made. All these insights are delivered on an intuitive dashboard that helps both healthcare professionals and individual users to track and understand skin health trends.

### II. LITERATURE SURVEY

J. Smith et al. [1] present an artificial intelligence-based tool for dermatological diagnosis using DCNN methods in conjunction with sophisticated image processing methods. It involves ROI marking, texture mapping, GLCM-based segmentation, Otsu's thresholding, and morphological operations. To improve the accuracy in classifying skin disorders, transfer learning using VGGNet was implemented. This approach was effective in melanoma detection as well as image processing speed. It does have some shortcomings, however, such as being dependent on image quality, needing manual segmentation, and thus not being fully adaptable to automated processes across diverse datasets.

A. Kumar et al. [2] created a diagnostic system using CNNs and transfer learning with a VGG16-based architecture aimed at differentiating skin lesions. To aid image quality, they employed histogram normalization techniques. The tool displayed a classification accuracy of 87.23%. While this suggests

potential to assist in under-resourced areas, the system is still limited by a lack of clinical validation and a narrow diseased skin model, which does not facilitate flexible application across diverse populations and unable under-tested skin diseases and conditions. The system did demonstrate 87.23% accuracy in classification which indicates potential use in health quirk regions. However, there are several obstacles that restrict its practical use, including the extent of disease coverage. Its dependence on big datasets and the need for more clinical validation to ensure it works well for all skin types and conditions. L. Huang et al. [3] investigated the application of AI in the analysis of dermatology images. They pointed out the importance of CNN models such as GoogleNet, ResNet, and DenseNet. Furthermore, they also explained the ways in which GANs can produce misleading fake lesions and how this can improve training (augmentation) and increase diversity in the models (variance). The authors described ensemble approaches along with transfer learning and explained how they may enhance the accuracy of diagnoses. Remote assessment enabled remote tests, sparing dermatologists relief, but results raised some concerns. They noted problems concerning dataset diversity and quality, the need for high-quality images, and ethical issues such as patient privacy, trust in AI systems, and trust in the technology used.

### III. METHODOLOGY

#### Step 1: Data Collection and Preprocessing

The AI model was trained on a labeled dataset containing images of skin conditions. Images were resized to 224x224 pixels and normalized to unify them. This process makes the data clean, normalized, and formatted for the training.

#### Step 2: Model Architecture

For the foundational model, the team selected a MobileNet V2 convolutional neural network (CNN) because it is both light and performs admirably with image classification tasks. To enable the model to classify images of skin conditions, the researchers changed the last classification layer append to skin affection. With this change, the model now estimates skin affections using images as inputs. **Step 3:**

#### Prediction Pipeline

An uploaded input image is first subject to some preprocessing and then is evaluated by the trained CNN model. The system then determines which class is the most likely match and provides a confidence score. [6] This score shows how certain the model is about its prediction, helping users gauge how reliable the result is.

#### Step 4: Explainable AI (LIME)

The LIME framework (Local Interpretable Model-Agnostic Explanations) is integrated with the pipeline to enhance explanation of models' automated decisions. Using heatmap imagery, LIME paints visual explanations to highlight how much impact particular regions of an image had on the model's prediction. This interpretive element enhances the tool's trustworthiness for clinical and general use.

#### Step 5: User Interface

The system's backend features a Gradio-based graphical user interface which permits the convenient uploading of dermatological images. During the procedure, the interface shows the predicted skin condition alongside its confidence level, the explanation map generated with LIME, and skincare recommendations. This design improves interactivity while maintaining simple access and ease of use for both the public and healthcare professionals.

### IV. RESULTS



Fig1: Medical Image Classifier

**Disease Name: Bowens**

**Confidence Score: 0.9888**

**Explanation:**

Explain the disease 50 Bowens Disease in simple terms. Generate according to: The skin is our largest organ a that it protects us from external factors such as bacteria, viruses, water loss etc. But did you know that your ai immune system? In fact, about two third of your entire immune system reside in your skin! This is why derma called "specialists of the immune system". The immune cells in the skin have a very important role to play – tl healthy by fighting against infection and cancerous changes. However, sometimes these immune cells can m instead attack normal healthy tissue leading to diseases like psoriasis or vitiligo (white patches on the skin). I will be discussing one such condition called Bowen's disease which affects approximately 1-2% of the popula 40 years old. It is named after Sir Thomas Brockiehurst Bowen who first described this condition in 1912. Bow type of non melanoma skin cancer arising within sun damaged skin. Non melanoma skin cancer refers to bas (rodent ulcer) and squamous cell carcinoma (Bowen's disease). Both types of skin cancer arise due to DNA da UV radiation from the sun and tanning beds. Unlike melanomas, these types of

**Personalized Tips:**

1. Protect your skin from UV radiation - Use protective clothing, hats, sunglasses, and broad-spectrum sunser at least 30+.
2. Regular self-skin examinations - Check your entire body regularly, especially any suspicious spots, and rep immediately if you notice any changes.
3. Quit smoking - Smoking increases the risk of developing Bowen's disease due to its immunosuppressive of
4. Maintain a healthy weight - Being overweight increases the likelihood of developing various types of cance Bowen's disease.

Fig2: Confidence Score

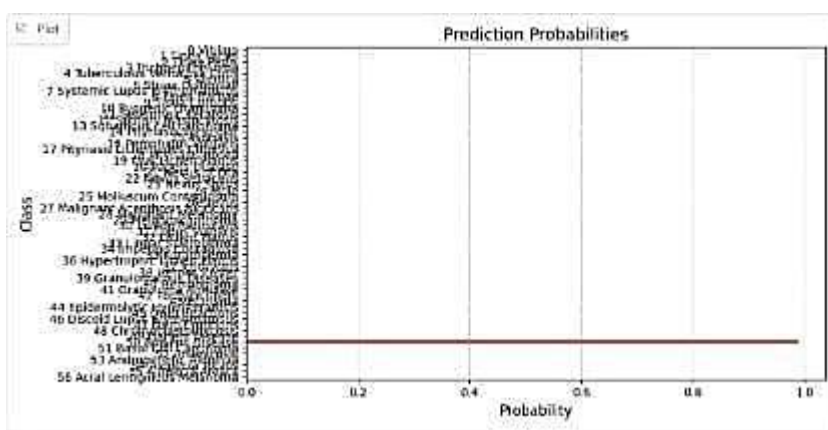


Fig3: Prediction Probabilities

V. COMPARATIVE ANALYSIS

S.NO	Model	Value
1.	AI Tool for Preliminary Diagnosis of Dermatology Manifestation(IJARIE, 2024)	The accuracy of this model is 87.23% (VGG16), 72.28%(Custom CNN)
2.	AI Based Tool for Preliminary Diagnosis of Dermatological Manifestations(IJRASET, 2024)	Accuracy is not exactly mentioned. But it has high accuracy.

VI. CONCLUSION

We incorporated an artificial intelligence technology, focused on medical application, to categorize and explain dermatological disorders as all-encompassing and systemized as possible within this work the proposed system uses explainable artificial intelligence (XAI) techniques such as LIME to enhance mobile diabetes unit and patient mobile assistant’s transparency about their workings alongside a clinical pre-trained MobileNetV2 model. The developed Gradio application allows the simple interaction with users through details of the diagnosis, observation-based confidence scores, and comprehensive visual explanations and detailed skincare recommendations. Moreover, output in the form of graphical class probability and heat map representation of machine model decision are intuitively reasoning supporting the understanding of model outcomes. This integrated formulation provides a foundation for the improvement of awareness of advanced practice providers and the clinical decision support system in dermatology at primary care levels.

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