Skin Disease Prediction using NASNet

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***Abstract*— In this paper, we propose a skin disease prediction system that utilizes deep learning techniques to classify skin lesions from images. The system is built on a dataset containing images of eight distinct skin diseases, which are organized into training and testing sets. We are using a range of pre-trained models and fine tuning it according to the dataset and using them for feature extraction and classification, achieving significant accuracy in disease prediction. The model is evaluated using standard metrics such as accuracy, precision, F1 score and recall. Our findings demonstrate the potential of the system to assist healthcare professionals in diagnosing skin conditions effectively and efficiently, thereby enhancing early treatment and improving patient outcomes. The developed system offers a user-friendly interface, allowing users to upload images and receive immediate disease predictions.**

I. Introduction

Skin diseases are increasingly prevalent and can significantly affect individuals' health and quality of life. Timely and accurate diagnosis is essential for effective treatment. Skin diseases are conditions that affect your skin. These diseases may cause rashes, inflammation, itchiness or other skin changes. Some skin conditions may be genetic, while lifestyle factors may cause others. Skin disease treatment may include medications, creams or ointments, or lifestyle changes [1].

However, skin problems are generally among the most common diseases seen in primary care settings in tropical areas, and in some regions where transmissible diseases are endemic, they become the dominant presentation. For instance, the World Health Organization's 2001 report [1] on the global burden of disease indicated that skin diseases were associated with mortality rates of 20,000 in Sub-Saharan Africa in 2001. This burden was comparable to mortality rates attributed to meningitis, hepatitis B, obstructed labor, and rheumatic heart disease in the same region.

Accurate and timely diagnosis is crucial in preventing complications and ensuring effective treatment. However, traditional methods of diagnosing skin conditions often rely on visual examination by dermatologists, which can be subjective, time-consuming, and limited by expertise. In rural and resource-limited settings, access to specialists is often scarce, exacerbating delays in diagnosis and treatment.

That's where deep learning comes into play. Deep learning, a subset of artificial intelligence, has demonstrated remarkable success in image recognition tasks, making it a promising tool for skin disease diagnosis. With the increasing availability of large datasets of medical images and advancements in computational power, deep learning models can now be trained to recognize and classify skin conditions with high accuracy.

II. Literature Survey

The authors in [2] discussed the complexity of diagnosing skin diseases due to diverse skin tones and visible effects of infections. It proposes integrating deep learning (DL) and machine learning (ML) models to enhance accuracy and speed in skin disease detection. The study utilizes three ML classifiers and four pre-trained DL models for feature extraction. ResNet50 combined with Support Vector Machine (SVM) achieved the highest accuracy at 99.11%. Limitations include the potential for a limited dataset affecting the model’s generalizability.

A. Singh et.al., in [3] developed a Skin Disease Classification Using Machine Learning Algorithms : This study emphasizes the need for automated diagnostic tools due to the complexity of skin diseases, often manifesting in tough textures and variable colors. Using the PH2 dataset with 200 dermoscopic images, the study applied four different classification techniques based on the ABCD rule. The main limitation is the relatively small and possibly non-diverse dataset, which restricts the generalizability of the findings.

In [4], authors developed A Method Of Skin Disease Detection Using Image Processing And Machine Learning: This study classifies skin diseases using a pre-trained AlexNet CNN and an SVM classifier. The combined dataset contained 20 images each of Normal, Melanoma, Eczema, and Psoriasis. The methodology includes preprocessing, resizing images, feature extraction using AlexNet’s convolutional layers, and classification using Multiclass SVM, achieving 100% accuracy.

The work of [5] proposed hybrid method combines the Structural Co-occurrence Matrix (SCM) for feature extraction and an enhanced Convolutional Neural Network (CNN) for classification. The model achieved 97% accuracy, while comparisons with FFT + SCM and SVM + SCM yielded lower accuracies. Limitations include potential overfitting in image processing and sensitivity to dataset quality.

M. Khan et.al., in [6] implemented pre-trained models such as VGG16 and VGG19 for skin disease detection, supported by SVM for classification. The VGG models achieved a Top-1 accuracy of 60% and a Top-3 accuracy of 80.3%. Limitations include the need for standardization across varied image dimensions in the dataset.

Authors of [7] explored the differences between machine learning and deep learning approaches for skin disease detection. The study compares techniques like SVM, KNN, and Ensemble Bagged Tree for ML, and VGG16, GoogleNet, and ResNet50 for DL. Both approaches yield satisfactory results, but the study lacks detailed accuracy metrics.

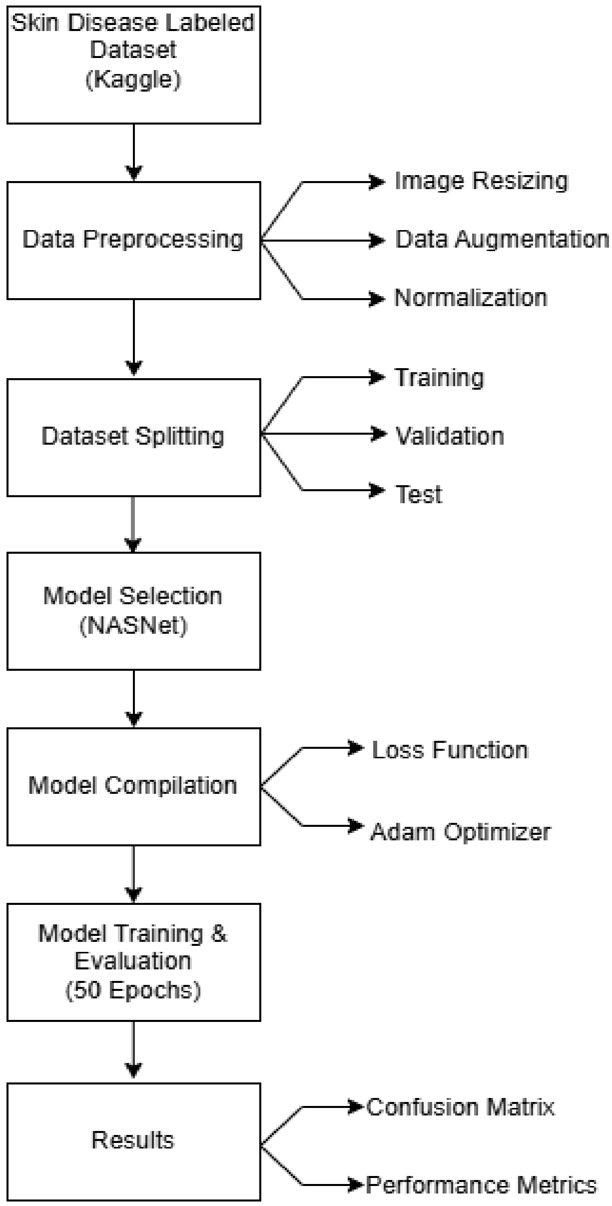
In [8], the authors proposed a system that combines CNNs for automatic feature extraction and SVM for classification, built into a mobile app. The model performed well in detecting diseases like eczema, melanoma, and psoriasis, with high accuracy rates. Limitations include image quality and less common diseases affecting performance.

J. Kim, the author of [9] discussed a system designed to detect and classify diseases using image processing techniques like contrast enhancement, segmentation, and feature extraction via Grey Level Co-occurrence Matrix (GLCM). Decision Trees are used for classification, achieving an accuracy of 87%. The system's limitations include dependency on image quality and the limited range of detectable diseases.

In [10] reviews advancements in deep learning for skin disease recognition, using datasets from hospitals and medical databases. Techniques such as data augmentation and deep CNN architectures like AlexNet and VGGNet are emphasized. The study reports high accuracy rates, often exceeding 94%, but notes limitations with pre-trained models and dataset diversity.

Authors of [11] proposed the use of CNN models for classifying skin diseases across diverse skin types. A diverse dataset, including images of different skin colors, ages, and lesion stages, was used for training. Although the study reported improved classification performance over previous models, it faced challenges with darker skin tones and overfitting risks.

III. METHODOLOGY



Data Preprocessing: The input to the model consists of skin images, resized to a standard size of 224x224 pixels to match the NASNet input requirements. The images are normalized by dividing pixel values by 255, scaling them between 0 and 1. A batch dimension is added to the image tensor before feeding it into the model.

Model Architecture: The NASNet model pre-trained on the ImageNet dataset was fine-tuned for the classification of skin diseases. The final layer of the pre-trained NASNet model was modified to output predictions for a set of predefined skin conditions, based on the training dataset.

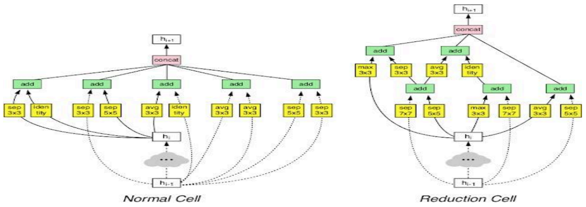


Figure 1: [13] Architecture of NASNet Model

Training: The model was trained using a dataset of labeled skin images, which included various diseases such as cellulitis, impetigo, athlete's foot, nail fungus, and more. Transfer learning was employed to leverage the pre-trained NASNet weights, while the final layers were trained on the skin disease dataset for better accuracy in this specific domain.

Inference and Prediction: Once trained, the model was saved and loaded for real-time inference. A user uploads a skin image through a Gradio-based interface. The image is preprocessed and passed through the model, which predicts the most likely skin disease. The prediction is returned as the name of the disease from the predefined categories.

User Interface: A Gradio interface was built for ease of use, allowing users to upload images directly and receive instant predictions. This makes the model accessible and interactive for non-technical users.

IV. Experiment

The dataset used for this project was taken from [11] which consists of 8 classes where each class consists of approximately 100 images.

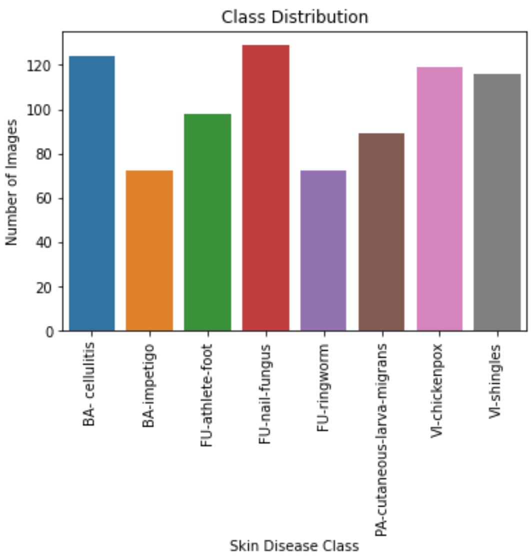


Figure 2: Distribution of images in the dataset

Figure 3: Example of an image from each class

V. Results and discussion

The results are based on a pre-trained model with minor modifications. The images are fed into our model and the rate of disease detection is generated as a result. All the eight types of diseases have different types of detection ratios, which might vary based upon the properties of the image as shown below.

	Precision	recall	f1-score	support
Cellulitis	0.88	0.88	0.88	33
Impetigo	0.95	1.00	0.98	20
Athlete Foot	0.89	0.97	0.93	32
Nail Fungus	1.00	1.00	1.00	33
ringworm	0.89	0.74	0.81	23
Cutaneous-larva-migrans	0.74	0.80	0.77	25
chickenpox	0.97	1.00	0.99	34
shingles	0.97	0.88	0.92	33
accuracy			0.91	233
macro avg	0.91	0.91	0.91	233
weighted avg	0.92	0.91	0.91	

Table 01: Classification Report

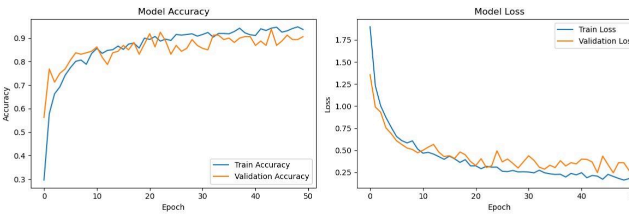


Figure 3: training and validation performance plot

The following confusion matrix was obtained after the training and validation of the model.

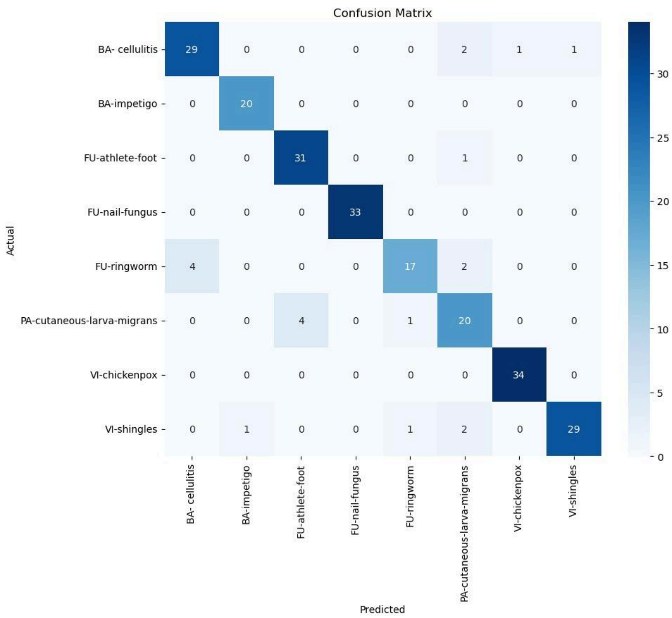


Figure 4: Confusion matrix

VI. Conclusion

In this project, we developed a skin disease prediction and classification model using the NASNetMobile architecture. The model was trained on a comprehensive skin disease image dataset, incorporating image augmentation techniques to improve generalization and robustness. To enhance predictive performance, we employed a fine-tuning approach, unfreezing certain layers of the NASNetMobile base model for additional training. The use of early stopping and a learning rate scheduler allowed for optimized training, minimizing overfitting while maintaining model accuracy.

Through extensive evaluation on the test set, our model achieved a satisfactory level of accuracy, demonstrating effective classification across several skin disease categories. Additionally, a Gradio-based user interface was implemented, enabling real-time image uploads for disease prediction. This interface provides an accessible tool for medical practitioners and individuals alike, offering a quick, automated approach to preliminary skin disease screening.

Overall, the project shows that deep learning models, when fine-tuned and trained on quality datasets, can provide accurate and efficient solutions for dermatological diagnostics. Further research could explore the expansion of the dataset to include more disease types and the application of explainability techniques to enhance model transparency in medical diagnostics.

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