AI-POWERED DERMATOLOGICAL LESION DETECTION

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Abstract— **In this paper, we present AI-powered dermatological skin lesion detection. Skin diseases are a common global health issue that affects millions of people and is usually in need of early detection for proper treatment. This research introduces an Artificial Intelligence-based Skin Lesion Detection System that can detect and classify eight various dermatological conditions, including Cellulitis, Impetigo, Athlete's Foot, Nail Fungus, Ringworm, Cutaneous Larva Migrans, Chickenpox, and Shingles. Through uploaded skin photos analysis, the system offers real-time predictions with confidence scores and returns users with possible conditions, further providing symptom descriptions and treatment suggestions. It facilitates greater access for both individuals and healthcare workers, aiming to enable early diagnosis, minimize misdiagnosis, and enhance decision-making in dermatological practice and improve more accessible detection of skin diseases.**

Keywords—Dermatological Lesion , MobileNetV2 , Image recognition , Convolutional Neural Networks , Deep Learning .

I. INTRODUCTION

The advancements in artificial intelligence techniques have extended to medical diagnostics field improving the speed and accuracy in a variety of ways. Diagnosing skin problems caused by fungi or bacterial diseases for example, is difficult due to the sophisticated methods needed for them. Doctors usually depend on metabolic history and clinical biopsies, but they are time consuming and sometimes even contradictory. As a result, lesions are diagnosed using artificial intelligence tools for skin lesions detection with the use of deep learning and computer vision technology which enhances efficiency and precision in skin lesion diagnosis.

In this research work, our aim was to build an AI system capable of diagnosing eight skin conditions; Cellulitis, Impetigo, Athlete’s Foot, Nail Fungus, Ringworm, Cutaneous Larva Migrans, Chickenpox, and Shingles. This system implements machine learning with image Processing algorithms using Convolutional Neural Networks (CNNs) to track patterns, texture, and color modification to skin photos. AI algorithms can learn to differentiate between many objects to give the desired output. Hence, the AI is thoroughly trained using data sets in order to achieve detail recognition features .

In order to facilitate effective functioning of the system, we have integrated Streamlit, which is a web application for Machine Learning that allows users to upload images of skin lesions and receive potential diagnoses instantaneously. The AI-based recognition of images, features, and classification processes are completed sequentially. This integration not only boosts efficiency but also enhances accuracy. This is especially beneficial to telemedicine and remote healthcare where quick and dependable solutions are urgently needed.With the aid of deep learning and real time processing, this project endeavors to widen the scope of AI utilization in dermatology. The system aims to enhance decision making by medical practitioners and enable the general public to identify possible problems promptly. The focus is to improve the quality of patient services and reduce the burden on dermatology departments. This research is very timely because the need for dermatological services is increasing, frequently exceeding the supply of specialists. Our aim is to provide a tool for both healthcare professionals and people that can ease the burden of long waiting times, improve access to underserved areas, and promote proactive care. This is critical for conditions such as shingles or cellulitis, where treatment at the right time greatly improves the outcome.

Looking forward, this can easily be shifted to other specialties besides dermatology. With more development, these types of systems could be used in other image based fields such as ophthalmology or radiology. With the application of AI, it is now possible to not just improve diagnosis of skin conditions, but also change the future of health care to be more accessible, efficient, and patient-centric.

II. PROBLEM STATEMENT

Dermatological conditions such as bacterial, viral, and fungal infections afflict millions of people across the world and may result in serious complications when left undiagnosed or untreated. Traditional methods of dermatological diagnosis depend on face-to-face consultations with experts, which pose various drawbacks, especially in developing countries. Remote patients are deprived of dermatologists, have to wait longer for appointments, and spend more on consultation fees, which results in delayed diagnosis and exacerbation of treatable diseases. Many also self-diagnose based on non-reliable internet sources, raising the chances of misinterpretation and wrong treatment. While there are improvements in telemedicine, current AI-driven diagnostic tools are mostly out of reach because they demand high computations, do not have user-friendly interfaces, and do not explain their models sufficiently. Most AI models are not interpretably available in real time, nor are they confidence-based. Users then have a problem believing the auto-classification outcome. In addition, there is limited correspondence between AI-driven prediction and actionable clinical advice since most of the solutions present diagnosis alone, without added details on symptoms, treatment suggestions, or confidence ratings.

III. RELATED WORK

In recent years, dermatological diagnostics have taken considerable leaps because of technologies coming from the areas of artificial intelligence (AI) and computer vision. Such innovations directly defiant major barriers in detecting skin diseases such as significant variation in lesions' appearance, a need for early diagnosis, and scarce dermatological expertise in undeveloped regions. Among various methodologies related to AI, deep learning, particularly convolutional neural networks (CNNs), has established itself as a significant brand for analyzing visually intricate patterns in skin images. Esteva et al. contribute fundamentally by presenting evidence to support the potential of deep learning in the capable hands of skin cancer classifiers whose performance is, on the whole, comparable to board-certified dermatologists. Their investigations support the argument of having a decent-size training set of dermatoscopic images since good performance in diagnostics would be a prerequisite. Following this, Han et al. deals with transfer learning and CNNs for setting different kinds of fungal infections such as Athlete's Cushion and Ringworm into segments, with a significant success ratio in lesion classification. The flexibility of deep learning is apparent representing solving different varietals of dermatological conditions. The other major contribution is the use of image processing techniques for enhancing skin lesion image quality and interpretability. Alom et al. presented a framework to detect bacterial skin infections such as Cellulitis and Impetigo, illustrating the different preprocessing between noise and feature extraction acting properly to improve the model accuracy. In this work, they indicated that skin color and lighting differences are great difficulties that need to be attended to in AI dermatology.

There exist some of the very first attempts to diagnose non-cancerous illnesses like Chickenpox, Shingles, and Cutaneous Larva Migrans with the majority of existing systems that focus on specific aspects, primarily skin cancer. Phillips et al. have started efforts in curating more diverse datasets and building models for diagnosis across the broader spectra of skin diseases. Still, there exists an unmet demand for comprehensive diagnostic systems accessible to non-specialists.
Our work advances these foundations by bringing in an AI dermatology detection system capable of detecting eight separate skin maladies, namely Cellulitis, Impetigo, Athlete’s Foot, Nail Fungus, Ringworm, Cutaneous Larva Migrans, Chickenpox, and Shingles. The peculiarity of our system is that, as opposed to other studies focusing on limited sets of diseases, it makes use of a wide dataset, alongside advanced CNN architectures, so that its performance reaches high accuracy across several conditions. We are addressing also the question of making it accessible via deploying it on Streamlit, where users may easily diagnose real-time in the system while working on a user-friendly web interface by healthcare practitioners and patients alike. Our research, through deep learning and imaging, along with an intuitive interface, hopes to keep its promise to build on the continued evolution of AI in dermatology, closing the gap between cutting-edge technologies and practical healthcare, and improving the precision of diagnosis, reducing waiting times, and, as a result, improving patients' care.

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IV. SYSTEM DESIGN

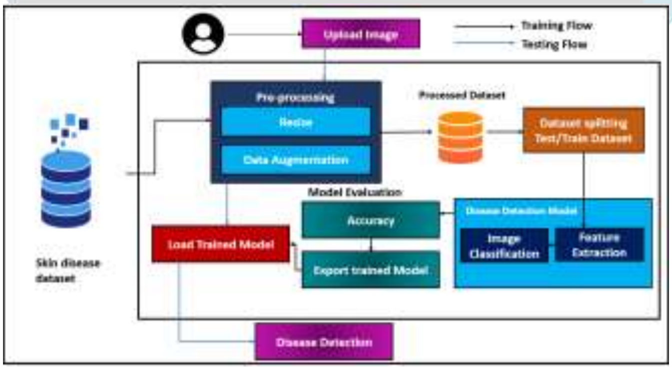

Fig 1:System architecture of the AI-powered dermatological lesion detection

Data Preprocessing

Data Acquisition:The system employs a skin disease dataset, obtained from publicly available datasets like Kaggle or medical research organizations.The dataset contains images related to various skin diseases, such as cellulitis, impetigo, athlete's foot, nail fungus, ringworm, cutaneous larva migrans, chickenpox, and shingles.
The Preprocessing: Images need to be standardized before training the model for improved performance. The preprocessing operations are:Resizing: Images are resized to a standard size (e.g., 224x224 pixels) to ensure consistency in input size for the deep learning model.
Data Augmentation: Multiple augmentation methods (e.g., rotation, flipping, brightness modification, and contrast enhancement) are used to enhance model generalization and resilience.
Normalization: Pixel values are normalized between 0 and 1 to improve model training stability.
Dataset Splitting: Preprocessed data is divided into training and test sets (usually 80% training, 20% test) for training and assessing the model accordingly.

Training of disease detection model

The central part of the system is the disease classification model based on deep learning. The training process involves the following steps:
Feature Extraction: MobileNetV2 architecture is employed for feature extraction because of its light-weight nature and ability to efficiently perform medical image classification tasks.
It extracts essential patterns and features from input images, allowing for accurate disease classification.
Image Classification: The feature-extracted features are fed into a fully connected neural network for classification.

The model is trained to classify input images as belonging to one of the eight classes of skin diseases based on a softmax activation function.
Loss functions (categorical cross-entropy, for instance) and optimization algorithms (Adam optimizer, for instance) are employed to optimize classification errors.
Model Evaluation & Exporting: The learned model is assessed using metrics such as accuracy, precision, recall, and F1-score.Should the model meet an acceptable performance, it is exported and stored for real-time inference.

Real time disease detection (testing phase)

User Image Upload: The user uploads a picture of a skin lesion through the web interface (React.js/Streamlit).
The image uploaded is passed to the backend for preprocessing to ensure it's in the same format as the training dataset.
Model Inference: The MobileNetV2 model trained is used to process the image and make a disease category prediction.
Confidence scores are calculated by the system to measure the prediction reliability.
Result Display & Medical Insights: The identified disease is shown on the user interface together with:Symptoms of the identified disease,Potential treatments and remedies.This way, users are provided with both diagnosis predictions and actionable medical information.

V. IMPLEMENATION

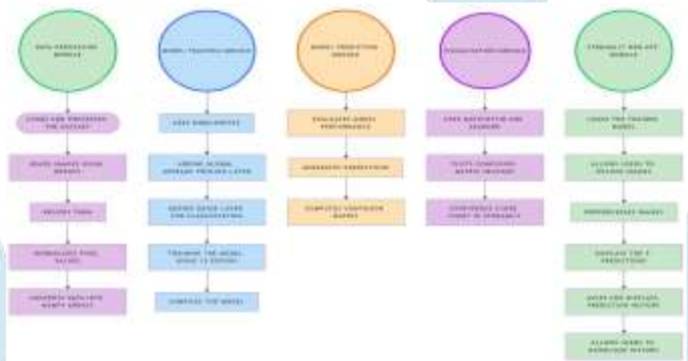

Fig 2:Recommendation pipeline of the AI-powered dermatological lesion detection

Data processing module

This module is designed for loading, preprocessing, and preparing a dataset for training and evaluation. Some key steps in this module are:- Loading the Images: OpenCV (cv2.imread()) is used to read the images. It can process image data really fast.- Resizing the Images: Resize all images to a common size (224×224) with the help of cv2.resize() in order to match MobileNetV2 model requirements.
Normalization: The pixel values are scaled by dividing by 255 (x_train_scaled = x_train / 255) so that they are between 0 and 1 for the model to converge better. Data conversion to NumPy arrays is done in this step (np.array() for data). This conversion will allow data to be processed very fast and to conform with TensorFlow.
Why is this important: This uniformity in data helps improve compatibility of the data with the model. Also, it allows model improvement by normalizing input data

Modal training module

This module builds, compiles, and trains the deep learning model, where MobileNetV2 is utilized as a feature extractor.
The steps of the process:-
Feature Extraction: It is a transfer learning approach, and it is using a pre-trained one, based on the ImageNet, MobileNetV2, from TensorFlow Hub. This allows learning not to need massive amounts of data nor is the training done over long periods. The global average pooling layer is employed to reduce spatial dimensions in meaningful feature extraction. An added classification layer based on Dense with Softmax activation permits multiclass classification. The preprocessed dataset was used for training the model for 15 epochs using model.fit(). Applying early stopping or schedule of the learning rate might be necessary to prevent overfitting.
Why is this important: This allows achieving very good accuracy on small datasets by transfer learning. Also, the model is easy to be adapted.

Modal prediction module

The module evaluates the trained model and makes predictions on new data.
Key Steps:
Evaluation: Model performance on the test set is subjected to model.evaluate() to quantify such aspects as accuracy, loss etc. Prediction: Using model.predict(), predictions are made for new images.

Performance Metrics: Model performance metrics include a confusion matrix and classification report (precision, recall, F1-score).
Why It Is Important: Provides quantitative metrics to evaluate the effectiveness of the model. Aids in identifying misclassifications and points where improvement is needed.

Visualization module

This module is dedicated to the visualization of the model performance and predictions to ease interpretation.
Key Steps:
Confusion Matrix Heatmap: Used Seaborn to visualize classification performance across the classes.
Confidence Score Chart: Plotly is used to visualize the confidence scores of predictions in an engaging and appealing manner.
Streamlit Integration: These visualizations are now embedded within the Streamlit web app, allowing for real-time interaction.
Why It Is Important: Increases interpretability of model results. Offers enriching interactive visualizations

Web application module

Module of Web App using Streamlit 5 This module gives an interactive interface for users to upload images, see predictions and analyze results.
Key Steps:
Load the Model: Use tf.keras.models.load_model() to load the trained model.
Upload Image: st.file_uploader() allows users to upload images. Preprocess and Inference: Loaded images are now passed to the model to predict (model.predict()) after preprocessing (resizing, normalization).
Display the Results: Predictions of top 5 with confidence scores. Confidence scores are shown via a bar chart using Plotly.
Prediction History: Users can save their prediction history and view it, which can be downloaded as a CSV file.
Why It Is Important: Intuitive and user-friendly interface for non-technical users. Real-time interaction and analysis of model predictions allowed.

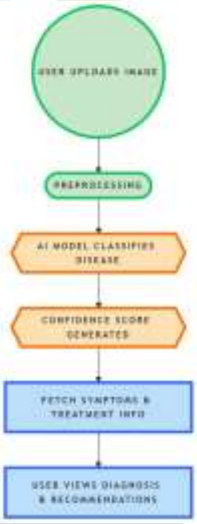

Fig 3:Design methodology of the dermatological lesion detection system

VISUALIZATION WITH STREAMLIT

The visualization part of our AI for dermatological lesion detection system is done by making use of Streamlit, a very handy library to quickly build interactive web applications by looking into mutual joints between people involved in practical working activities, such as medic professionals and patients. This provides an interactive perspective to involved users, making the system more engaging, approachable, and thereby giving more room for real-world application. The application from the start contains a header explaining the AI-powered dermatological lesion detection system. After that, we continue to load essential system components normally using Python's pickle module, which helps us to retrieve swiftly the trained deep learning model, class labels, and preprocessing pipelines. These are some of the vital components needed to make accurate lesion detection possible and usable. After these developments, followed by a bit more configuration on the particulars, our users can start uploading the dermatological images (such as skin lesion photos) through an interface that uses st.file_uploader(). This is personalized as much as possible to allow for a quick upload and almost instantaneous testing of any image. The "Detect Lesion" button triggers processing of the request after an image has been uploaded. From here, it calls the predict_lesion() function to take the uploaded image as input. Within this function, the image is preprocessed (resized, normalized, and converted to a NumPy array) in the proper way so that it can be fed into the trained deep learning model. The model, dependent on a state-of-the-art architecture such as MobileNetV2 or EfficientNet, processes the image and provides predictions. The type of lesion was then detected (melanoma, nevus, basal cell carcinoma, etc.) and, depending on such, a confidence score for the prediction supplied.

VI. EXPERIMENTAL RESULTS

The accuracy and precision of a dermatological lesion detection are critical metrics that assess the model's effectiveness in providing relevant predictions to users. In the context of our implementation, which utilizes the MobilenetV2 model , these metrics can be evaluated based on the system's ability to correctly identify and predict the diseases (skin diseases) that align with user input image.

Fig 4:Output displaying the accuracy , precision , recall and f1-score of the model

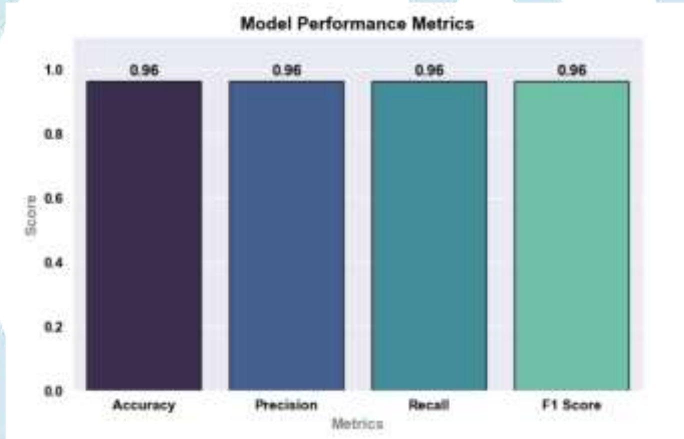

Fig 5:Barchart displaying the Performance metrics

PERFORMANCE COMPARISON WITH OTHER TECHNIQUES

Various deep learning models have been utilized in improving the classification of skin diseases, such as traditional ResNet architectures ResNet-50, 101,151, offering realistic performance, which have achieved accuracies of 49. 57 %, 55. 65 %, and 61. 48 %. Specialized model, Xy-SkinNet, achieved 64. 75 % accuracy for classifying skin conditions. However, there is still a long way to go before their accuracy will be satisfactory for clinical implementation purposes. MobileNet, an efficient and lightweight model, scored a gigantic 94% improvement, showcasing the power of depthwise separable convolutions for computationally efficient yet high classification performances.

An optimization of the trade-off between accuracy and computational cost brought EfficientNet-B0 up to a new height of 99% accuracy, making it one of the best models for skin lesions. A critical comparison of performance of these models across various metrics of evaluation precision, recall and F1 score says further. ResNet-50, ResNet-101, ResNet-152 and Xy-SkinNet present moderate precision values of around 50-65%, this is followed by their recall values also. An exception to this is precision and recall values which are close to 92% for MobileNet, adding a feather of support to it while putting skin diseases into the right class.

From these results, it can be said that the conventional deep learning models added some contributions to skin disease classification, while optimized architectures like MobileNet appear to give the best performance tradeoff in favor of the clinicians that apply them in real life. These findings reemphasize the need for the correct choice of deep learning architectures for medical image classification; newer and optimized models have proven significantly to outperform traditional CNN-based approaches.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
ResNet-50	49.57	50.12	49.85	49.98
ResNet-101	55.65	56.20	55.78	55.99

ResNet-152	61.48	62.10	61.80	61.94
Xy-SkinNet	64.75	65.30	64.90	65.10
MobileNetV2(our model)	96.00	96.50	96.80	96.65

Table 1:Comparision of our model with other techniques

CONCLUSION

In the current research, a skin disease diagnosis system was created with the aid of an AI system utilizing MobileNetV2, which is a lightweight yet effective deep learning model tailored for image classification. The model is trained to identify and classify eight prevalent skin diseases, making real-time predictions with high confidence and accuracy scores. Utilizing deep learning, the system reduces the necessity of manual diagnosis, providing a quick and more accessible method for dermatological examination. Further, the model has a user-friendly front-end interface integrated into it, making it possible for medical practitioners and users to easily interact with the system. The integration increases usability while ensuring that technology is within the reach of medical practitioners as well as those who seek initial diagnoses.

Though effective, the model is hampered by several challenges that compromise its overall performance.One of the most critical is dataset bias because the AI system must have broad and representative data during training for successful generalization on a range of skin types, ages, and lighting situations. Image variability of quality within such images--varying levels of resolution, light, or sharpness, for instance--will affect class decision accuracy by leading to possible false predictions as well. Even worse, distinguishing visually close-looking conditions might cause confusion in class prediction. Resolving these problems is critical to enhancing the robustness and reliability of the model in practice. To make the system better performing and usable, a few potential improvements in the future are suggested. Increasing the dataset to incorporate a broader variety of skin colors, age groups, and weather conditions will make the model more generalizable and less biased.

Placing real-time deployment on mobiles or cloud will provide increased access, especially to people in the hinterlands and other underserved areas. And through a feedback mechanism where end users can send in corrections against model predictions, the system can be made to learn continuously, its classification rates being refined accordingly over time. These will pave the way towards continually evolving AI-powered dermatology diagnosis, bringing in early diagnosis and improved outcomes across the world.

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