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DermAI : AI Based Skin Disease Classifier

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***Abstract*:** Skin diseases represent one of the global health issues with high prevalence rates, and early identification by appropriate diagnosis can help prevent complications and increase success rates. However, conventional skin disease diagnosis by dermatologists is a highly intensive and subjective process, especially in remote regions with scarce dermatological knowledge and skills. As such, this study proposes an automated skin disease classification systemäs based on EfficientNet-B0). This proposed model uses dermoscopic and clinical skin images and requires resizing, normalization, and data augmentation as part of its image preprocessing techniques to enhance its generalizability and robustness levels. Additionally, despite using skin lesion images for training and identifying their corresponding essential features using transfer learning techniques for training, this proposed automated skin disease classification system has demonstrated capabilities to significantly improve accuracy rates at lower precision, recall, and F1-score values compared to conventional CNN models and also provide faster training and inference speeds in its experimentation and validation phases. This also demonstrates that it would be highly beneficial for use in remote regions where skin lesion image classification can be performed in real-time due to its lightweight capabilities and high accuracy rates offered by EfficientNet-B0).

Keywords: ai-based skin disease classification, artificial intelligence, deep learning, machine learning, convolutional neural networks, medical image analysis, computer-aided diagnosis, dermatology, image classification, healthcare automation.

I. INTRODUCTION

Skin problems also form some of the most widespread health concerns across the world, and they affect individuals of all age groups. Obtaining an accurate diagnosis in a short period of time is crucial in efforts aimed at providing a remedy and in the prevention of complications such as infections, chronic diseases, and skin cancer. Historically, diagnoses in relation to skin diseases have been based on what the doctor sees and knows about dermatology. The challenge comes in considering the efforts involved in this hands-on method and its dependence on the availability of enough qualified doctors, especially in remote locations. Recently, advancements in the field of Artificial Intelligence and deep learning have opened the door for the development of algorithms capable of analyzing images. Artificial Intelligence-Assisted Skin Disease Classification uses digital skin pictures with skin lesions to classify skin diseases. The program utilizes convolutional neural networks (CNNs) to automatically extract features of color, texture, and shape from these pictures. Here, the objective is to develop an intelligent system that assists dermatologists in making informed decisions. techniques of image normalization as well as image augmentation techniques are utilized in the proposed model in order to increase robustness. models with advanced computational capabilities like EfficientNet models are utilized in the proposed system. The proposed system aims to deliver fast, accurate, as well as economically feasible solutions. Finally, the proposed project utilizes artificial intelligence in order to promote dermatology by increasing accuracy rates while decreasing diagnostic times. The model is quite user friendly and scalable and thus easy to integrate with healthcare applications on both smartphones and online platforms. The model is capable of performing early skin disease detection. This is vital for superior treatment outcomes. The model connects intelligent processing with domain knowledge to enhance dermatology assistance and accessibility.

II. LITERATURE SURVEY

[1]A study conducted by Dr. Hong Qing Yu of the University of Derby in the U.K. involved testing six deep learning models on the HAM10000 dataset using a Keras GPU environment, focusing on preprocessing and crossvalidations. The study then proposed the concept of the TwoPhase Targeted Ensemble Machine Classification Model (TEMCM). This is a dynamic ensemble that combines different models to improve accuracy in the classification of skin diseases utilizing the IoT environment. [2]Zhe Wu, Shuang Zhao, Yonghong Peng, Xiaoyu He, Xinyu Zhao, Kai Huang, Xian Wu, Wei Fan, Fangfang Li, Mingliang Chen, Jie Li, Weihong Huang, Xiang Chen, and Yi Li investigated the performance of five deep learning models on a total of 2,656 images in the Xiangya-Derm dataset concerning facial skin diseases. The best result was obtained by the use of the Inception-ResNet-v2 model. It is evident that deep learning techniques have made a significant impact in the field of medical image classification. With advancements in technology, better accuracy is bound to be achieved. There is still a need to develop models that automatically identify skin conditions. [3]Authors affiliated with HKUST, China, and Agency for Science, Technology, and Research (A*STAR), Singapore, Yijun Yang, Huazhu Fu, Angelica I. AvilesRivero, Carola-Bibiane Schönlieb, and Lei Zhu, proposed the use of DiffMIC. Based on diffusion, it has dual-granularity conditional guidance that merges global and local priors. This diffusion model relies on MMD regularization, which helps to maintain mutual information, and it has been trained on diverse sets of data, performing well compared with the stateof-the-art CNN and transformer networks. [4]Kumar and Patel's 2024 work explores AI-driven career guidance and student profiling. The work focuses on developing smart, adaptive systems capable of providing personalized career recommendations to individuals based on their abilities, areas of interest, academics, personality, and ever-changing preference. With the integration of machine learning, natural language processing, and data analytics, these platforms learn from user interaction, assessment, and feedback to make changes in suggestions based on need and time. The adaptive systems leverage insights mined from large datasets regarding job markets, educational pathways, industry trends, and skilled demands to suggest fitting career options, learning resources, certifications, and development plans tailored to the individual. In contrast to traditional counseling that is restricted to classrooms, largely static, and often limited by human availability, AI-powered guidance provides scalable, real-time, and more objective support. However, issues on data privacy, algorithmic bias, transparency, and the necessity for human oversight remain essential considerations to ensure that such personalized AI career guidance develops and serves ethically and with efficiency.

III. EXISTING SYSTEM

The clinical knowledge and ocular observation of dermatologists are the mainstays in a traditional approach to skin disease diagnosis. The

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procedure usually involves observing the color, form, texture, size, and distribution of skin lesions, which in many cases is supported by a dermoscopic examination and history of patients. The demerits of this approach are manifold though it is quite reliable when done by trained experts. A diagnosis might have variable accuracy depending on the dermatologist's expertise and skill level. Manual diagnosis consumes much time and may not be feasible in the areas where dermatologists with requisite training are few in number. There might be a subjective inconsistency in ocular-based diagnoses due to inherent subjectivity. The chances of delaying treatment might arise because accurate ocular detection of early-stage skin conditions may pose a challenge. Before the introduction of deep learning, several traditional machine learning methods were utilized for identifying and categorizing skin diseases. Some of the common algorithms used are SVM, KNN, Decision Trees, and Random Forests. These methods depend on features created manually, which include edge-based features, form descriptors, color histograms, and texture features like GLCM and LBP. These features, after manual extraction, are fed into a classifier. Though traditional machine learning models perform well, they still have numerous drawbacks. Their feature extraction requires heavy preprocessing and is domain knowledgeintensive. Performance depends much on the quality of handcrafted features. It is difficult for these models to generalize for a wide range of complex skin diseases. In recent years, deep learning, particularly Convolutional Neural Network (CNN), is a popular and established approach for detecting skin diseases, as it is highly interpolated utilizing advancements in the field of artificial intelligence. People use transfer learning from established pre-trained networks such as VGG16, ResNet50, InceptionV3, AlexNet, and DenseNet. In fact, all of these networks overcome the need for manual extraction of features from skin images, as it extracts hierarchical features from skin images automatically. Furthermore, when compared to conventional machine learning, it is likely to exhibit increased accuracy, improved robustness to variability in image quality, and better capability to pick out minute differences in patterns for the different skin diseases. Some of the advanced frameworks segregate the detection of skin diseases into two steps: carving out the lesion from the surrounding healthy skin and then running a classifier on the isolated area. Thresholding, region-based approaches, morphological operations, or U-Net segmentation techniques are practically used in segmenting the lesion. Once the lesion is clearly outlined, it proceeds to the predictive model to decide on the disease that might be present. Segmentation-based systems have their advantages. They zoom in on the region of interest, reduce background noise, and often enhance accuracy of classification. These come at costs: they make the workflow more complicated; they are slower processes because they involve multiple stages; poor segmentation decisions can lead to degradation in final prediction accuracy. While segmentation can improve performance, it is not necessarily the best choice regarding applications where real-time results or limited resources are involved. Another major barrier in the current work of skindisease diagnosis is the limited dataset coverage. Most publicly available datasets cover only a few conditions, usually five to ten classes like psoriasis, melanoma, nevus, and eczema. Other dataset issues include imbalance, since most datasets have more samples from lighter-skinned individuals, bias in skin tone, little variation in image quality, lighting, and age groups. These factors further limit how well the models generalize or are dependable in clinical settings. Dataset fairness and diversity remain a prime challenge for research.. This proposed project uses an AI system that classifies skin diseases using the advantage of transferlearning and a deep-learning architecture that is able to overcome the constraints. The system does not require the segmentation of the lesions and thus reduces the computation cost and the execution time.

IV. PROPOSED SYSTEM

The key objective is to provide recognition of multiclass skin diseases with automation, in order to enable further diagnostics to be faster, consistent, and even more accessible, even in resource-constrained environments lacking dermatological expertise. The system is engineered to provide high accuracy with low computational resource requirements, making it suitable for deployment over the web and mobile platforms, either in or near real-time situations. The architecture is divided into four major modules: data acquisition and preprocessing, the EfficientNet-B0-based classification engine, user interface with a recommendation layer, and logging and analytics. The inputs include dermoscopic and clinical images through public datasets and user uploads, which are fed into the EfficientNet-B0 classifier backend and sent back to the client with a predicted disease label and confidence scores along with some other related medical information, while all interactions are securely documented for historical reference and model improvement.

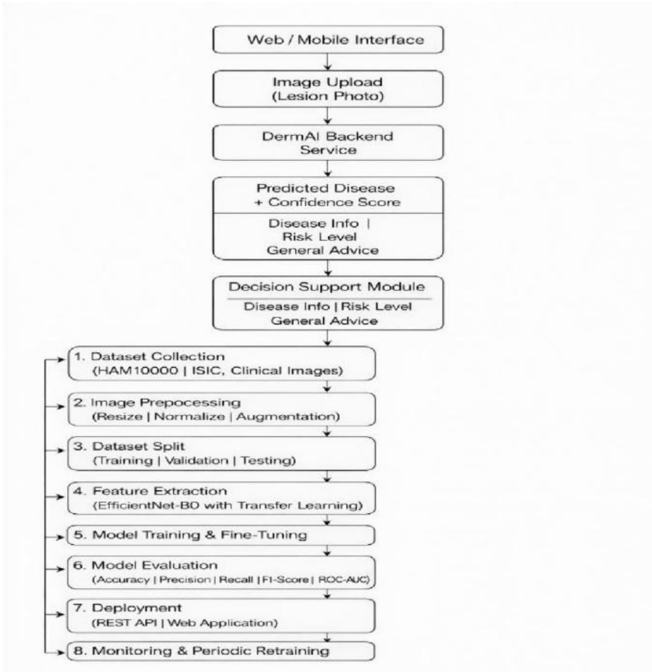

Figure 1: Sequence diagram

The main engine instantiates an ImageNet-pretrained EfficientNet-B0 as a feature extractor and adds a customized classification head consisting of global average pooling, dense layers, dropout, and a softmax output for the target disease categories. Training is done in two steps: first, training the newly added head layers and, second, fine-tuning some upper blocks of EfficientNet-B0 with weighted crossentropy to deal with class imbalance; its performance is then evaluated in terms of accuracy, precision, recall, F1-score, and ROC-AUC, similarly to modern EfficientNet-based skin disease analysis systems. Once a model is developed, an interactive interface is built on top of the model, resembling a "Skin Classifier" web dashboard. One can upload lesion images, trigger inference, and immediately view the predicted class, top-k alternative diagnoses, and confidence scores. Further, additional panels are used to inform about diseases, risk levels, typical symptoms, general treatment options, and explicit medical disclaimers. User profiles, statistics of scans, and gamified achievements enable personalized educational recommendations, with care not to replace professional diagnosis.

All predictions, including timestamps and confidence metrics, are stored in a secure history module that can be used by users and clinicians to review prior scans and can also facilitate the retraining and evaluation of model performance in the future. By design, the architecture is extensible, allowing integration with explainable AI techniques such as Grad-CAM visualizations and additional models in subsequent work to improve both accuracy and interpretability.

V. SYSTEM IMPLEMENTATION

In this regard, the DermAI system is designed as an end-toend AI-driven medical image analysis platform to provide accurate, real-time categorization of skin diseases while retaining usability, efficiency, and

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clinical relevance. The proposed system has a modular design consisting of submodules responsible for image acquisition, preprocessing, deep learning-based categorization, interpretation of results, and user interaction. The overall architecture is highly focused on scalability, reliability, and low computational overhead, thus appropriate for real healthcare settings.

1)User Interface and Image Acquisition Layer

A simple and easy-to-use environment for skin disease analysis is offered by the DermAI user interface, which is developed as a React-based Single Page Application (SPA). The interface presents diagnostic outputs in an easy-tounderstand manner while minimizing user effort.

It oversees:

- Drag-and-drop image uploading or file selection with real-time format and size checks.
- Reset and re-upload options are available in the live preview of the uploaded image.
- Uploading, processing, and analysis completion are examples of real-time status indicators.
- Predicted disease, confidence score, Top-K alternative predictions, and medical disclaimer are displayed in panels.
- Daily, weekly, and monthly prediction summaries are displayed on the history dashboard.
- JWT-based session tokens are used for secure API interactions with the backend.

2) OpenCV and PIL Image Capture and Preprocessing

Users upload dermoscopic or clinical photos to the backend in JPEG or PNG format. The preprocessing module prepares the images for effective deep learning inference.

The preprocessing step performs the following:

- scaling the image to the 224 x 224 pixel model input size.
- Scaling of pixel intensities and colour space conversion: normalizing RGB
- Noise reduction and slight suppression of artifacts are used where necessary.
- Consistency tests are needed, rejecting corrupted or wrong pictures.

Examples include rotation, flipping, zooming, and brightness normalization used during training as optional augmentation to enhance generalization.

3) EfficientNet-B0 Feature Extraction

The feature extraction engine employs the EfficientNet-B0 convolutional neural network on every image it processes.

- ImageNet-pretrained EfficientNet-B0 backbone extracts hierarchical visual features, such as color patterns, abnormalities of lesion texture, form, and boundary.
- Only the convolutional feature maps remain once the initial classification layer is removed.
- The classification head takes the extracted features as input for disease predictions.
- High accuracy at low computational cost can be achieved by this method.

4) Categorization and Disease Prediction

A unique classification head is used for the multi-class skin disease classification on top of the extracted feature vectors. Global Average Pooling reduces geographical dimensions while preserving semantic information. Fully connected layers with dropout regularization avoid overfitting. A Softmax output layer generates class probabilities for each disease category.

Prediction classifications are established as:

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- The disease with the highest confidence score is the main prediction.
- Top-K Predictions list the next most likely diseases for transparency.
- Confidence levels show the prediction reliability.

5) Decision Smoothing and Inference Logic

To ensure uniform and reliable predictions,

Outputs with low confidence are filtered through probability thresholds.

- Confidence values and the predictions are recorded for later evaluation.
- Optional ensemble averaging may be performed when analyzing many images of the same lesion.

This reasoning helps in enhancing diagnostic consistency and avoiding misleading results.

6) Alert and Recommendation Service

The Recommendation and Alert Service converts the AIbased predictions of diseases into insightful and approachable advice. It motivates users to take immediate medical action without causing unnecessary worry, and it helps them interpret their results accurately.

- Predicted disease labels and confidence scores are assessed. Conditions are then classified as low, moderate, or high in terms of severity.
- General precautionary and skin-care recommendations are provided. Advisory alerts are triggered in the case of low confidence or high-risk cases.
- Professional dermatological consultation is advised where necessary. Visual notifications are showcased using banners or toasts. Repetitive alerts are avoided by cooldown logic.
- The logging of alert events for session analytics is done. Confidence values are showcased for transparency.
- Medical disclaimers are shown to avoid misuse.

7) Chatbot Assistant

The Chatbot Assistant is a conversational AI module developed to increase user understanding and engagement by responding in simple medical language to customer inquiries regarding diagnoses.

- It takes user input in the form of natural language, applies prediction context to produce relevant answers.
- Describes what a disease is, its symptoms, and general causes; minimizes medical jargon for readability.
- Proposes further course of action without prescriptions, reinforces the need for a doctor/medical professional when required.
- Maintains conversational context at the session level, handles normal ergonomic-style health queries, does not make speculative medical statements, and stores anonymized chat logs for improvement.

8) Sessions and History Manager

The Session and History Manager keeps all diagnostic activities in organized records. It facilitates the observation of possible condition changes over time and the reexamination of previous assessments.

- A session is created for every analysis of an image.
- It stores the timestamp, the label of the disease, the confidence score, associates sessions with anonymized user IDs.
- Displays a chronological diagnostic history, enables comparing of many sessions, generates sessionlevel summaries, filtering by date and/or condition is supported.
- Access to sessions is secure, retrieval effort is kept to a minimum, and raw medical images are not stored.

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9) Data Store and Models

This module manages system data securely and effectively through Models and Data Store. It prioritizes scalability and privacy, with the guarantee of storage in a structured manner.

- Uses relational databases such as SQLite or PostgreSQL.
- Separates user metadata from the predictions.
- Keeps prediction and session records Logs chatbot interactions for analytics.
- Indexes frequently accessed fields.
- Provides support for fast aggregations of data.
- Precludes permanent storage of uploaded images.
- Uses anonymization methods in general Scales on the fly Has been designed with privacy-by-design principles.

10) Security, Privacy and Performance

This module makes DermAI run effectively, safely, and morally. By upholding dependability and user confidence, it enables real-world implementation.

- Low latency inference is optimized.
- CPU/GPU resources are used efficiently.
- HTTPS communication is enforced, and JWT-based authentication is implemented.
- User input in all forms must be validated. Data retention limits data to that which is necessary.
- Sensitive user information shall be safeguarded.
- Provide explainable AI outputs, confidence indicators, and adhere to ethical AI standards.

VI. RESULT

The paper presents the features and performance of the proposed skin disease classification model using AI.

Figure 2: Core AI-assisted diagnosis screen

This interface represents the central AI-assisted diagnostic interface. This allows you to upload your skin lesion image, which could either be dermoscopic imagery or clinical images, and initiate the diagnostic process. The primary interface features the skin lesion image that you have picked, and when you click on "Analyze Image," it runs server-side inference from the classification model EfficientNet-B0. Alternatively, to perform a fresh analysis, you can select "Reset." The Prediction Results are featured at the bottom of the interface, showing you the predicted disease. This constitutes the primary diagnostic output.

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Figure 3: Initial upload dashboard

This is a the initial upload screen before it proceeds to analyze anything. You can upload your photo in one of two ways: by dragging and dropping your photo or by browsing for one that meets size criteria. Below your upload card, according to your direction, you would see an "About This Classifier" card that lists the essential information: accuracy rate, number of classes supported for a disease model, and training data size. It provides a description stating that this classifier uses a deep learning model based on EfficientNetB0 and a balanced skin disease dataset due to its strong ability for applicability at a massive scale.

Figure 4: Prediction summary panel

This is the screen which provides an initial glimpse of the "prediction summary" panel that appears immediately as soon as the model has completed its processing on the selected lesion image input. Initially, the top section will highlight the primary predicted disease identity, complete with a bar representation and actual percentage of model confidence, thereby providing an immediate insight into model certainty levels for the classification outcome. Further, there is also an indication of the "Top-3 predicted classes," which indicates model confidence levels through corresponding "Progress bars," also highlighting "Processing time" taken for execution, and clearly visible "Medical disclaimer."

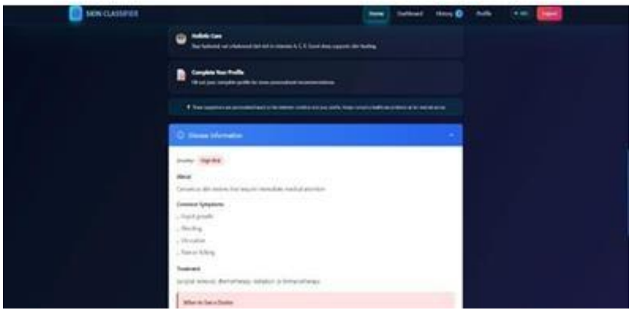

Figure 5: Disease information and recommendation panel

This view portrays the disease details and the recommendation panel that pops up after a prediction is made. It brings into view the severity of the condition that might be predicted and briefly describes the disease in text, including symptoms one can look out for and the general trends of treatment. The interface also points out when one should seek medical care and gives general wellness tips, emphasizing that the tool is not to replace professional medical help and consultation.

Figure 6: Prediction history module

Here, the prediction history display screen appears. It stores previous classification results to allow them to be inspected afterwards. Every record contains a thumbnail image of the analyzed lesion, the inferred disease name, the date and time of prediction, and a confidence measure. There are additional buttons to filter and sort records and another button labeled 'Clear All'. Finally, a disclaimer appears below that declares that all prediction results are only for educational use and must be interpreted by professionals.

Figure 7: User profile and personalization dashboard

This is the profile and personalization dashboard. Starting at the top, it provides a convenient summary of a profile information as a user, including number of scans performed, confidence level of model scans, number of high accuracy predictions made, as well as weekly profile activity level. Under that, there are structured fields where there is personal information as well as skin profile details (skin types/skin tone). On the other side, the dashboard displays your personal recommendations and achievements area. With such a system in place, the likelihood of continuous usage and relevant educational feedback increases significantly.

VII. CONCLUSION

Advanced convolutional neural networks, in particular, EfficientNet-B0, can move beyond mere experimental validation and become dependable, practical decisionsupport tools for dermatology, as demonstrated by the DermAI project. The model forms a solid generalization across multiple skin disease categories and achieves strong performance in classification tasks by leveraging a carefully curated and enhanced set of skin lesion images. Its lightweight architecture and streamlined inference pipeline make it suitable for a wide range of deployments on web and mobile health platforms, thus offering real-time predictions on moderately powered devices.

DermAI focuses beyond technical performance to emphasize human-centered design and ethical AI. To aid users and clinicians in understanding the results, it returns not just predictions but also confidence levels, alternative potential diagnoses, and clinical context in words. By offering sessionbased record tracking, with personalization through user interaction patterns driving that personalization, and explicit medical advisories and disclaimers, the system is designed to enhance and not replace expert dermatological judgment. It has demonstrated its feasibility to accelerate diagnostic workflows, widen access to dermatological knowledge, and help well-informed clinical decisions.

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