**Intelligent Chatbot-Assisted Deep Learning Framework for Skin Disorder Recognition and Personalized Healthcare Recommendations**

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**Abstract.** Developed a skin disease detection platform based on deep learning to facilitate real-time diagnosis and treatment recommendations. Integration of chatbot functionalities and disease progression tracking with an interactive dashboard enables user support and detailed feedback in real-time. Central to the system is the robust classification framework built around three deep learning models—AlexNet, MobileNet, and a custom Sequential model. Extensive evaluation conducted has shown the Sequential model to be the most effective with an astounding accuracy of 98% along with unparalleled dominance in precision, efficiency, and computational scalability. Beyond the chatbot, the platform is also equipped with a self-exploratory interactive dashboard that intuitively displays the diagnostic results, confidence scores, disease history, and even provides automated treatment suggestions. This enables both users and healthcare practitioners to monitor treatment and make informed decisions based on historical disease data. Simplifying navigation guides the users so that they can access the information required promptly. This multi-faceted approach improves the ability to use the system and receive diagnosis guidance in real-time while also making automated care more human. With the utilization of deep learning, the platform shows the potential AI has to transform the management of skin diseases. Automated precise classification using a Sequential model, combined with real-time interactions via a chatbot and dashboard, allows for scalability and consistency while prioritizing the user for timely, personalized attention, and thus better overall patient care. In dermatology, deep learning systems with 98% accuracy and rapid response times are unprecedented.

# **INTRODUCTION**

The robust capabilities of convolutional neural networks (CNNs) are leveraged in the sequential model framework to construct a skin disease detection and management system. Focused on the best possible diagnostic outcome, the system is designed to identify numerous skin diseases. Advanced learning strategies, such as multitask learning and few-shot learning, help sustain the model’s efficacy under sparse data conditions.

The platform includes capabilities of disease management and classification. When integrated with a knowledge base, the system diagnosing and managing skin pathology does not stop at identification but also offers management suggestions aimed at effective control of the disease. In addition to medication, prescribed treatments, and key actions to be undertaken, the diet prescribed will also contain instructions on avoidance. This approach provides for timely guidance in terms of meaningful suggestions provided alongside diagnostic results, thus enabling proactive measures and sustained intervention.

Likely referring to artificial intelligent (LAI) models real world diagnostic impact is broadened by multitask capabilities which improve generalization to new cases and reduce overfitting. Also, recognition of rarely seen diseases with minimal sample input is facilitated through the parallel implementation of few-shot learning. These combined improve the model’s performance in diverse clinical environments where large labelled datasets are rarely available. Integration of in-depth learning into self-directed health systems augments the domains of tele dermatology and integrated medicine with this platform. It offers remote consultation services that are patient-centered, easy to trust, and expand effortlessly without adding strain to traditional clinical practices. Moreover, the model helps patients actively by providing self-care instructions, thereby improving health outcomes. As stated, the model implements latest CNN technology which improves the accuracy of skin disease detection while outlines a detailed management plan tailored to each patient. This system also extends the availability of expert dermatology care and increases its value.

# **RELATED WORK**

Gulzar et al. [1] work pioneered automated skin diagnosis with advanced machine and deep learning applications. Along with Asif et al. [2], who created CFI-Net, ensemble learning based model designed to diagnose various skin diseases which increased classification, these systems enhanced performance further. Hossen et al. [3] examined the impact of Xception deep learning architecture on dermatological condition detection and noted its streamlined efficiency and accuracy. Understanding the lack of privacy-preserving frameworks, the author suggested a model where skin disease diagnosis algorithms could collaboratively train on many devices, improving privacy and model accuracy simultaneously.

To deal with the intricacy of an accurate diagnosis, Balasundaram [4] devised a stacking-based ensemble method that is optimized with a genetic algorithm which dramatically improved accuracy by utilizing several base models in conjunction with one another. Lee et al. [5] worked on mobile healthcare applications by creating a multitask, few-shot learning framework for effective skin disease recognition using minimal training samples, which is beneficial in resource strained settings. In her work on novel diagnostic approaches, Naqvi et al. [6] studied the dielectric properties of skin lesions in depth, working towards more accurate diagnostic methods.

Riaz et al. [7] to work on skin cancer early detection developed a dual task feature extraction and classification unified joint learning model. Almufareh [8] designed an edge computing framework to support real-time melanoma detection on portable devices, making early diagnosis more accessible. Albahli et al. [9] integrated the YOLOv4-DarkNet detection model with active contour methods to enhance the segmentation and detection of melanoma lesions. Lastly, Mohanty et al. [10] provided a comprehensive review of various analytical frameworks aimed at addressing challenges in skin disease diagnosis, especially under constraints such as limited datasets.

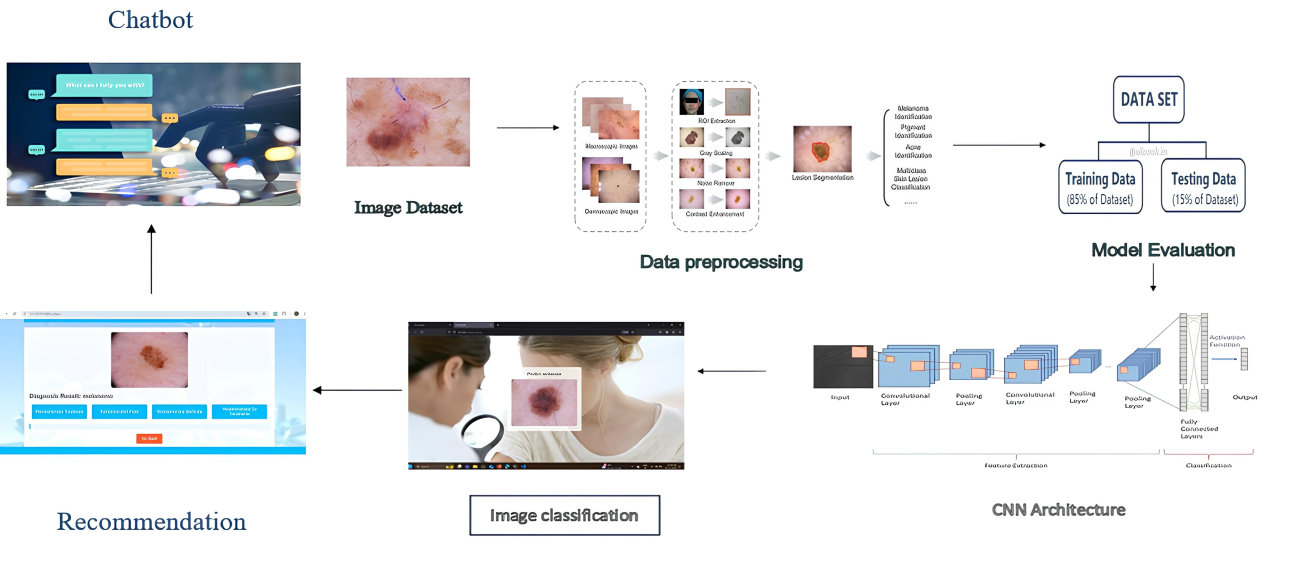
Yeo et al. [11] Handles small, imbalanced datasets for skin lesion classification using a single deep learning model with optimized training. Kumar et al. [12] combines mixed-domain hand-crafted features with multiheaded CNNs for enhanced skin disease recognition. Xiao et al. [13] Introduces FS3DCIoT, a few-shot incremental learning model for differential diagnosis using consumer IoT. Ji et al. [14] Develops EFAM-Net with attention and enhanced feature fusion for multi-class skin lesion classification. Pham et al. [15] Improves classification performance using custom loss functions, balanced mini-batches, and real-time augmentation.

# **PROPOSED SYSTEM**

Traditional methods of skin disease diagnosis rely heavily on expert visual assessment, which can vary between practitioners and may lead to inconsistencies in treatment. To address these issues, we have developed an AI-powered platform that enhances the accuracy and efficiency of skin disease diagnosis. This system uses advanced image processing and deep learning models to analyse skin conditions from uploaded images. The AI is trained on a large dataset of dermatological cases, enabling it to identify a wide range of skin diseases with high precision. Proposed system is an automated artificial intelligence system designed to assist with deep learning of skin diseases through a complete detection framework as illustrated in Figure 1. It integrates deep learning and convolutional neural networks into a sequential model immersed within a designed architecture. This model permits the linear placement of layers, rendering design and training easier. Analysing images is easy for CNNs because they effortlessly pull salient features from skin images without any prior work. This allows the system to capture and identify the intricately patterned skin lesions that might be associated with multiple dermatological conditions.

CNNs are particularly efficient at image analysis because they automatically retrieve important aspects of skin pictures without any preprocessing, which enable the system to identify complicated skin lesions suggesting multiple dermatological conditions. For more precise diagnostics, the system employs sophisticated learning techniques like multi-task and few-shot learning. In particular, multi-task learning affords controlling diseased patients while recommending appropriate treatments or dietary suggestions, therefore improving the model’s multifunctionality. Few-shot learning prepares the system to function well, even when there is minimal training data available, which is useful for uncommon skin disorders with limited image data available.

The designed system makes certain that the user’s accessibility requirements are adequately addressed. Users have the capability to submit images of their skin issues and, in return, receive a diagnosis along with step-by-step tailored guidance in a matter of minutes. This feature enables proactive skin health management to be practiced and early interventions to be obtained, particularly for those who do not have the means to see a dermatologist promptly. In general, the goal of this platform is to improve the relative and absolute diagnostic accuracy and quality of patient care given through intelligent dermatological tools with relation to their wide use.



**FIGURE 1.** Architecture diagram of skin disease detection

## **Data Acquisition and Processing**

A compilation of hospital and publicly available databases provided images containing a diverse collection of dermatological conditions. Images underwent a pre-processing stage which included resizing, contrast enhancement, and noise removal to streamline the image retention processes and ensure high quality inputs for models training.

## **Feature Engineering**

Critical visual patterns and textures were captured to form the dataset used within the classification models in a form of reproduced morphologic features as the most discriminative elements.

## **Model Development**

A model with sequential architecture was developed based on the CNN structure through stacking convolutional, pooling, and fully connected dense layers. Several sophisticated training approaches such as multitask learning were added to better the model performance and generalization in smaller datasets.

## **User Interaction**

The model was processed into a simple web application interface where users can interact with the model by uploading images of skin conditions or skin problems.

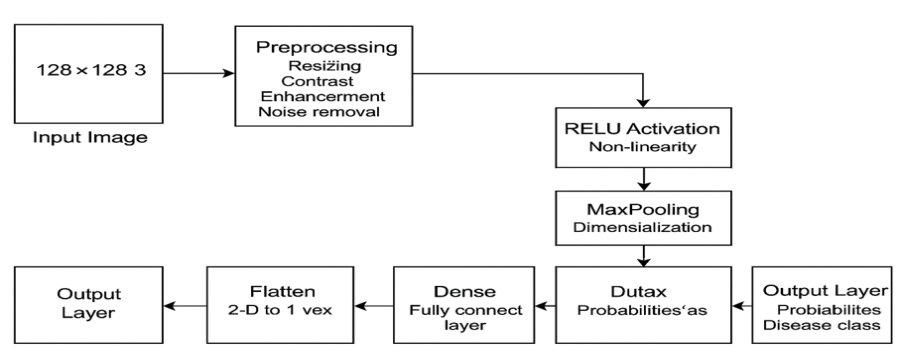
# **SEQUENTIAL CONVOLUTIONAL NEURAL NETWORK MODEL**

In a Sequential Convolutional Neural Network (CNN) model, the input image III of shape (H, W, C) (H, W, C) (H, W, C) (e.g., 128×128×3 for RGB) is passed through a series of layers to extract features and classify the image as presented in Figure 2. The mathematical expression for this process is represented in Equation (1) as follows.

|  |  |
| --- | --- |
|  | (1) |

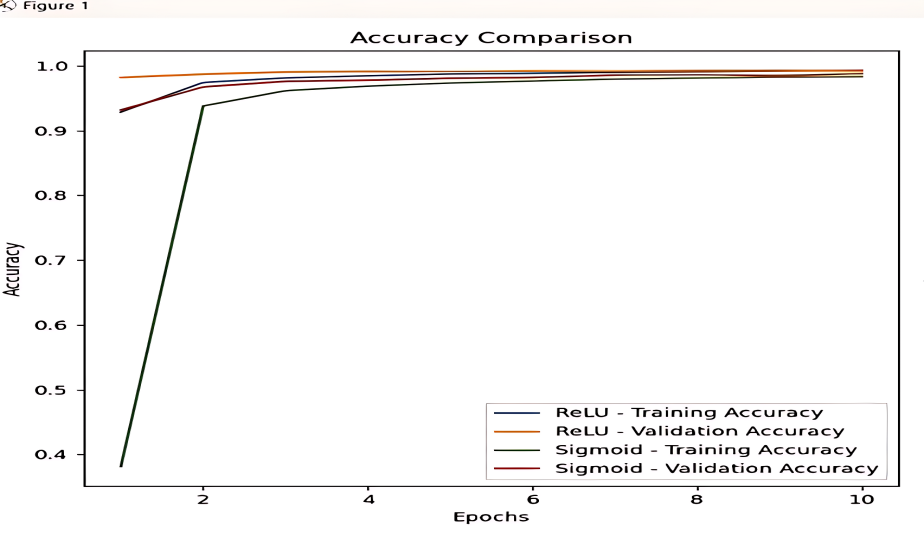
Where:

* C1,C2C\_1, C\_2C1,C2 are convolution operations with different filters and depths,
* ReLU\text{ReLU}ReLU applies a non-linear activation: ReLU(x)=max⁡(0,x)\text{ReLU}(x) = \max(0,x)ReLU(x)=max(0,x),
* P1,P2P\_1, P\_2P1, P2 are max pooling layers that reduce the spatial size,
* Flatten\text{Flatten}Flatten converts the multidimensional feature map into a vector,
* D2D\_2D2 is the dense (fully connected) layer,
* SoftMax\text{SoftMax}SoftMax maps the output to probability scores across disease classes.



**FIGURE 2.** Working process of convolutional neural network

This pipeline enables the model to learn hierarchical feature representations, starting from edges and textures to high-level features, and ultimately outputs the predicted class label of the skin disease. Validating a CNN model with a confusion matrix offers insights into classification performance, highlighting correct predictions and misclassifications. It reveals true positives, false positives, true negatives, and false negatives. This aids in evaluating precision and recall, helping fine-tune the model for improved accuracy and generalization on unseen data. Figure 3 shows the comparison between ReLU and Sigmoid function.

**FIGURE 3**. Accuracy comparison between ReLU and Sigmoid function

The graph provided in Figure 3 compares the training and validation accuracy of ReLU and Sigmoid activation functions over 10 epochs. ReLU consistently shows higher and more stable performance, with both training and validation accuracies nearing 98%. Sigmoid starts lower but improves quickly, though it slightly underperforms ReLU in final accuracy.

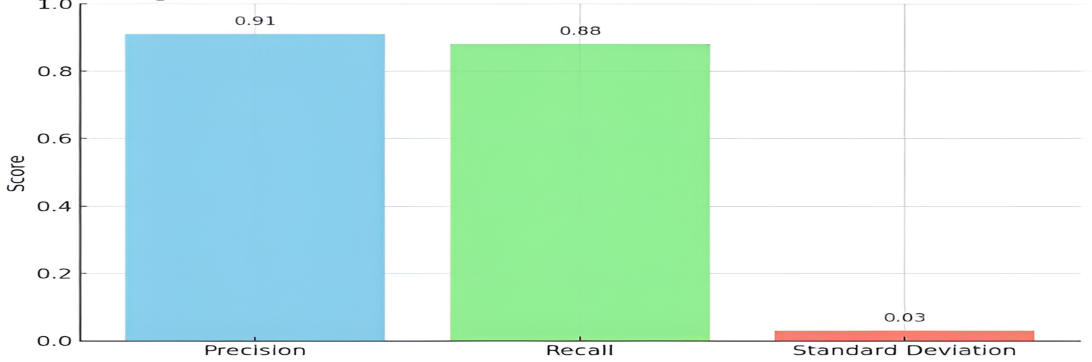
Table 1 compares the ReLU and Sigmoid activation functions in terms of training and validation loss. ReLU shows consistent learning with stable loss values, while Sigmoid starts with low training loss but increases over epochs, indicating instability. ReLU performs better overall, suggesting improved convergence and generalization compared to Sigmoid.

# **RESULTS**

A sequential model applies to image datasets by feeding the input pixel data through several layers through which the data has to pass. The layers are trained to learn and classify features of the image. Usually, the process starts with Conv2D layers which receive the image. Several filters are applied through Conv2D layers to gather low and high level features, changing between edges, textures and shapes. These features are important for distinguishing between different classes. Following the convolution, layers called MaxPooling2D are used to downscale the spatial size of the output. Because the feature maps contain important information, a reduced spatial size will lessen computation and prevent overfitting. As information travels deeper into the network, it captures more complex patterns. The feature maps are 2D, and the network needs 1D data, thus, the Flatten layer which 2D to 1D feature maps converts will suffice. These Dense layers classify as the learned features are explicated and a probability score for each class label is assigned. Back propagation is one of the processes employed to train the model. It compares the predicted outputs with actual expectations and computes the difference using a defined loss function. To decrease loss, the model reweights its internal structures using optimization algorithms like Adam, SGD, etc. After a number of epochs and validation, the model is able to improve on its performance and attain high accuracy on images that were not seen before.

| **TABLE 1.** Comparison of activation loss function | | | | |
| --- | --- | --- | --- | --- |
| **Epochs** | **ReLU - Training Loss** | **ReLU - Validation Loss** | **Sigmoid – Training Loss** | **Sigmoid – Validation Loss** |
| 1 | ~ 0.93 | ~ 0.98 | ~ 0.36 | ~0.95 |
| 2 | ~ 0.96 | ~ 0.98 | ~ 0.93 | ~0.96 |
| 4 | ~ 0.96 | ~ 0.98 | ~ 0.96 | ~0.97 |
| 6 | ~ 0.99 | ~ 0.96 | ~ 0.97 | ~0.97 |
| 8 | ~ 0.99 | ~ 0.96 | ~ 0.96 | ~0.98 |

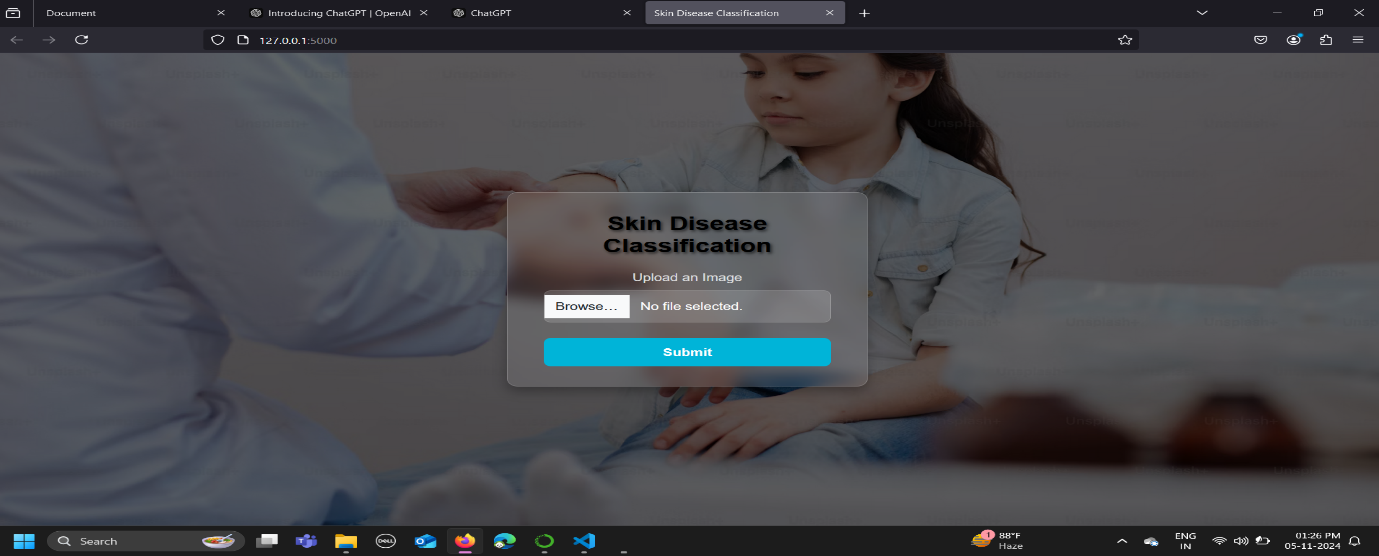
Figure 4 contains a bar graph with a classification of a skin disease model that shows some actual performance measures. It is a good insight to the model trustworthiness. From the graph, the precision score of 0.91 shows that a model user will successfully predict a skin disease with a skin disease 91% of the time. This indicates good competency to minimize false positives, which is very important when dealing with medical diagnostics, as falsely diagnosing a patient can result in the patient receiving the wrong treatment. On the other hand, the recall score of 0.88 indicates that the model captures 88% of the actual diseased cases which are a good ability to gauge the true positives, so the ability to gauge the true positives with high recall guarantees accuracy on cases that are actual and are very important.



**FIGURE 4.** Performance analysis of proposed model

The sequential model achieved an accuracy of 98%, surpassing Alex Net and Mobile Net. Moreover, the model demonstrates a low standard deviation of 0.03 across different batches or subsets of the dataset. This low variability emphasizes the model’s reliability and steadfastness in performance, suggesting that it adapts well to new, and unseen data. Low deviation reinforces the model’s robustness, suggesting that the model’s predictions are not greatly influenced by shifts in the input data. Collectively, these metrics—high precision, high recall, and low standard deviation—high deviation together illustrate a well-balanced and reliable model trustworthy for deployment in skin disease detection where accuracy and duplicated reliability are critical requirements.

The system shown in Figure 5 has an interface which is user friendly because it allows users to upload an image for skin disease classification. An upload box which is centrally located enables users to pick any image they have in their devices. The classification procedure is started using a clearly marked “submit” button. As soon as an image is submitted, the system evaluates the image with a trained model to predict possible dermatological issues. The system provides results immediately, so users can access some initial insights about their possible conditions. The ease in navigation as well as the orderly arrangement of elements on the interface allow users who are not experts in the field to use the system. This enables them to seek some guidance before they see a physician.



**FIGURE 5.** Web interface design for skin disease prediction application

The interface displays a skin disease diagnosis result as in Figure 6, which identifies the disease as basal cell carcinoma. It provides tailored recommendations via buttons for treatment, diet, medication, and oil remedies. Beneath, the food suggestions such as berries, salmon, and avocado help bolster skin health, enhancing patient care by integrating diet.



**FIGURE 6**. Food and precautionary recommendations interface

# **CONCLUSION**

The proposed chatbot-integrated Sequential CNN framework presents a robust solution for real-time skin disease identification and personalized healthcare recommendation. Its high predictive accuracy, coupled with a seamless user experience, positions it as a vital tool for improving dermatological healthcare accessibility and effectiveness. Future developments will involve expanding model complexity through ResNet architectures and attention mechanisms, enhancing mobile compatibility, and integrating user-driven feedback loops to refine system intelligence.

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