

skinova

AI-Powered Dermatology Assistant

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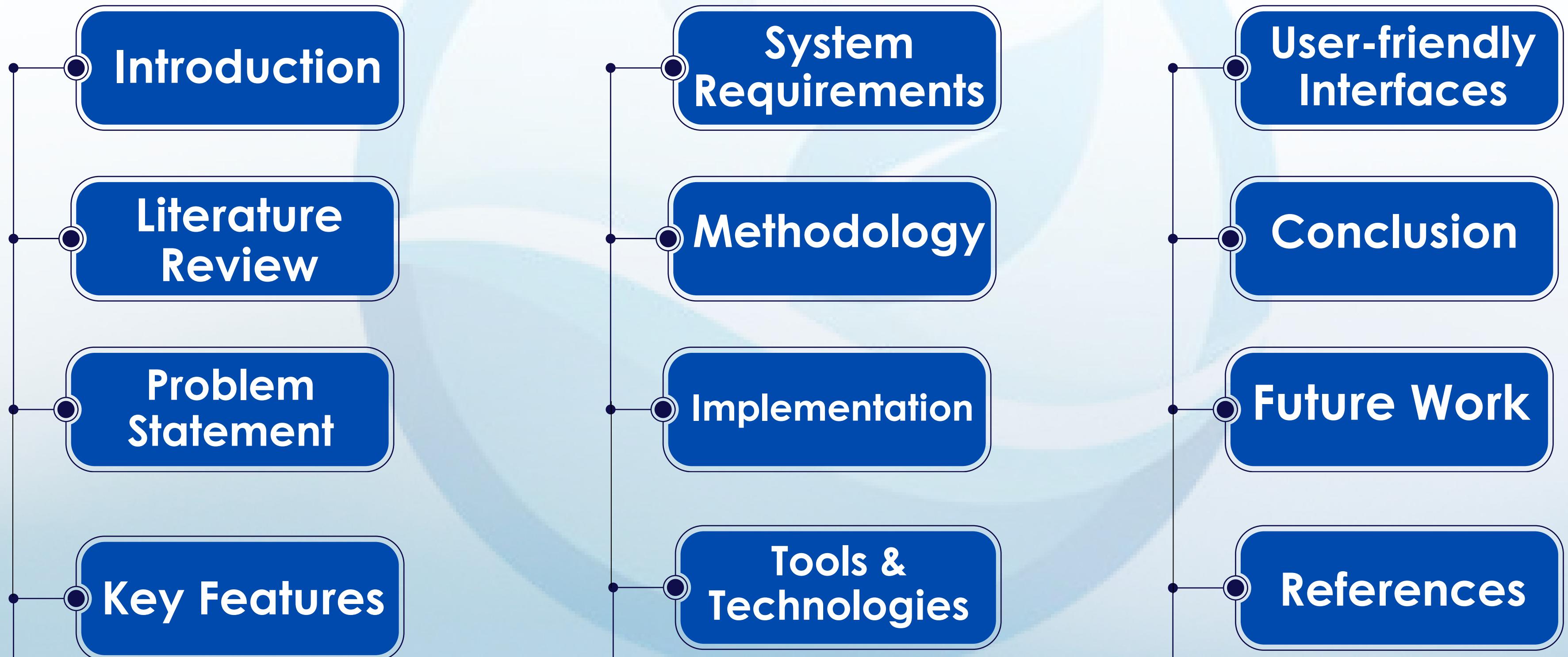
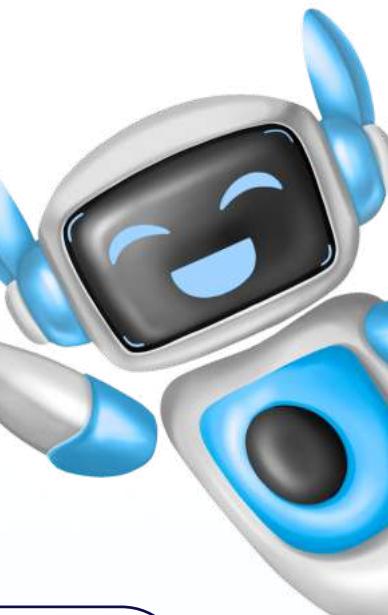
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Overview





Introduction

Skin diseases are among the most prevalent health problems worldwide, ranging from common conditions like acne and eczema to serious and life-threatening diseases such as melanoma. Despite their widespread impact, many cases remain underestimated or misdiagnosed, especially in regions with limited access to specialized dermatological care.



Dermatological diagnosis is a challenging process that relies heavily on visual examination and clinical expertise. Many skin diseases share similar visual patterns, which increases the risk of misdiagnosis even for experienced dermatologists. These challenges may result in delayed or inappropriate treatment, potentially leading to disease progression and preventable complications.

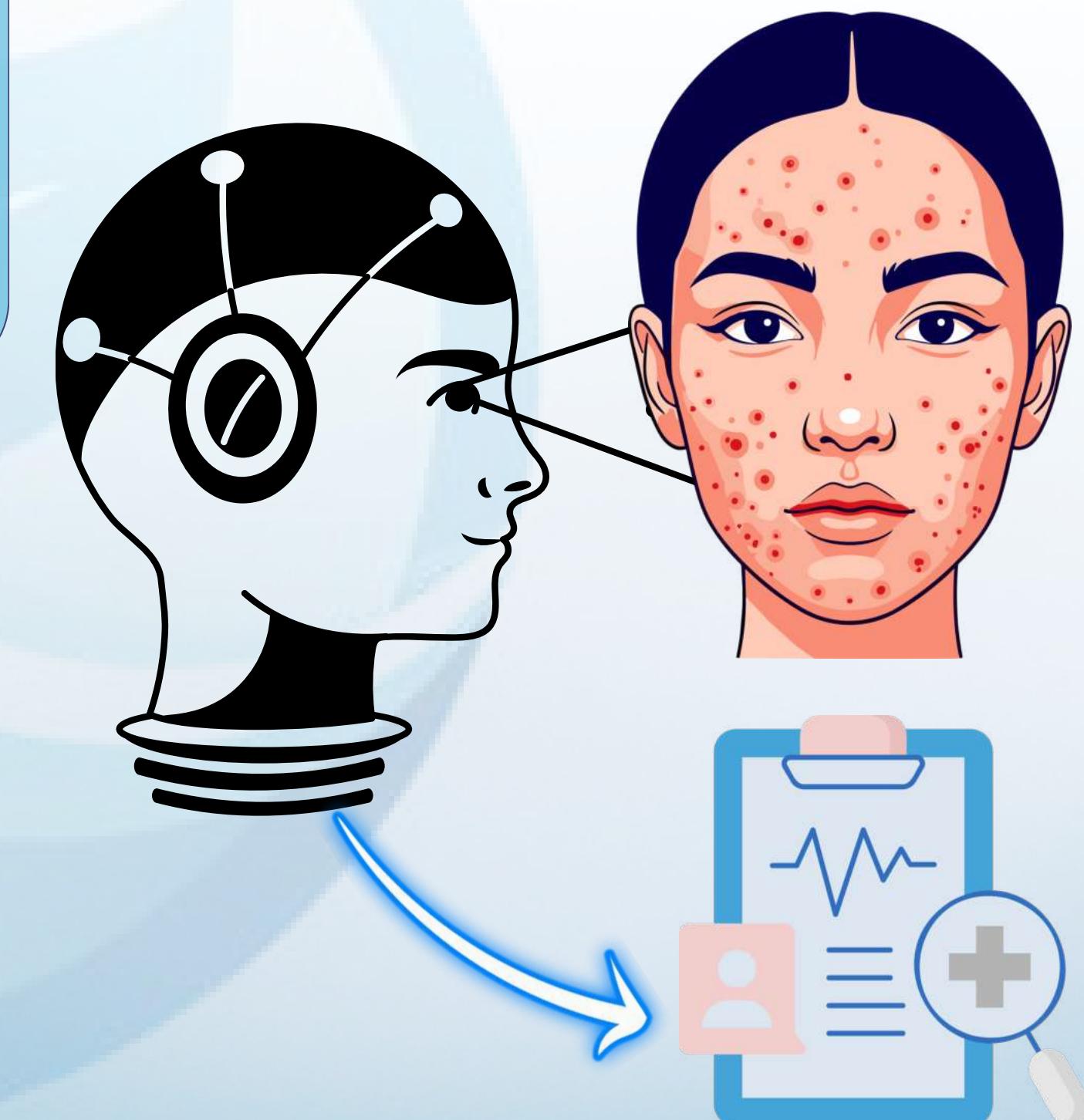




Introduction

In recent years, advances in Artificial Intelligence, particularly Deep Learning and Convolutional Neural Networks (CNNs), have significantly enhanced medical image analysis. These models can automatically learn complex visual features from large datasets, enabling accurate detection of subtle patterns in dermatological images that may be difficult for the human eye to recognize.

The integration of AI into dermatology has the potential to improve diagnostic accuracy, reduce human error, and increase accessibility to preliminary medical assessment. AI-powered systems can assist healthcare professionals by providing a second opinion, and they can also help patients in remote or underserved areas gain faster access to dermatological insights. However, despite these advantages, many existing AI solutions remain limited in scope and practicality.

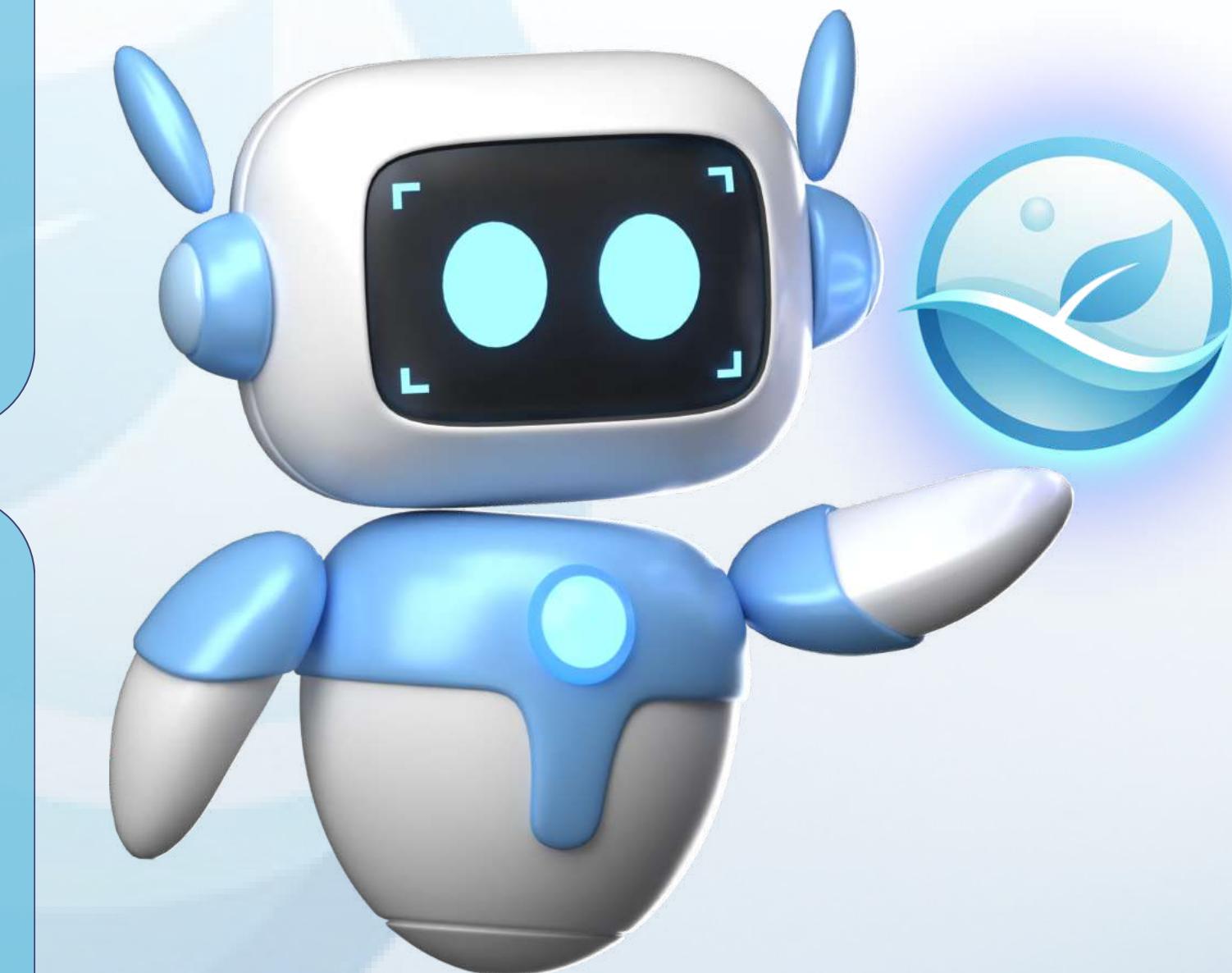




Introduction

This project introduces SKINOVA, an AI-powered dermatology assistant designed to provide accurate skin disease classification while addressing real-world medical safety concerns. Unlike traditional AI-based diagnostic systems that focus only on disease detection, SKINOVA aims to combine deep learning-based image analysis with medical decision support to create a more comprehensive and reliable solution.

The primary objective of this project is to develop an intelligent system that supports early skin disease detection, improves diagnostic confidence, and enhances patient safety. By leveraging advanced deep learning techniques and integrating medical knowledge, SKINOVA seeks to bridge the gap between academic research and practical healthcare applications. This system is not intended to replace dermatologists, but rather to act as an assistive tool that supports informed medical decision-making and promotes safer treatment practices.





Literature Review

Several studies have focused specifically on the classification of dermatological disorders using deep learning architectures. In 2023, a study titled “Deep Learning Based Classification of Dermatological Disorders” investigated the performance of multiple CNN models, including ResNet, VGG, and EfficientNet, on skin disease datasets. The study demonstrated that deep learning models can achieve high classification accuracy when combined with proper preprocessing and data augmentation. Despite these promising results, the system was limited to disease classification and did not integrate medical knowledge related to treatment or patient safety.

Biomedical Engineering and Computational Biology

► [Biomed Eng Comput Biol. 2023 Jul 31;14:11795972221138470. doi: 10.1177/11795972221138470](#)

Deep Learning Based Classification of Dermatological Disorders

Lulwah AlSuwaidan ^{1,✉}

► Author information ► Article notes ► Copyright and License information

PMCID: PMC10392223 PMID: [37533697](#)

Abstract

Automated medical diagnosis has become crucial and significantly supports medical doctors. Thus, there is a demand for inventing deep learning (DL) and convolutional networks for analyzing medical images. Dermatology, in particular, is one of the domains that was recently targeted by AI specialists to introduce new DL algorithms or enhance convolutional neural network (CNN) architectures. A significantly high proportion of studies in the field are concerned with skin cancer, whereas other dermatological disorders are still limited. In this work, we examined the performance of 6 CNN architectures named VGG16, EfficientNet, InceptionV3, MobileNet, NasNet, and ResNet50 for the top 3 dermatological disorders that frequently appear in the Middle East. An Image filtering and denoising were imposed in this work to enhance image quality and increase architecture performance. Experimental results revealed that MobileNet achieved the highest performance and accuracy among the CNN architectures and can classify disorder with high performance (95.7% accuracy). Future scope will focus more on proposing a new methodology for deep-based classification. In addition, we will expand the dataset for more images that consider new disorders and variations.

Literature Review

More recent research has attempted to improve classification performance through optimized and hybrid deep learning models. In 2024, the study “Accurate Deep Learning Algorithms for Skin Lesion Classification” proposed advanced CNN architectures using transfer learning techniques. The results showed notable improvements in classification accuracy across multiple skin disease classes. Nevertheless, the study acknowledged that high model performance alone is insufficient for real clinical deployment without incorporating medical context, treatment guidelines, and safety considerations

Accurate Deep Learning Algorithms for Skin Lesion Classification

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Abstract:

A skin lesion is any irregularity or alteration to the texture, color, or appearance of the skin. It arises from a number of skin illnesses, such as malignancies, autoimmune diseases, allergies, and infections. Early detection and precise diagnosis of skin lesions are crucial for effective treatment and management of these disorders. Dermatologists and other healthcare professionals have traditionally diagnosed skin lesions through visual inspection. However, using this approach might result in a delayed or incorrect diagnosis. Skin lesion categorization accuracy has significantly improved as a result of recent advancements in deep learning techniques. This study looks at the different deep learning techniques used to classify skin lesions. These include transfer learning (DenseNet201 and ResNet52V2) and convolutional neural networks (CNNs). Our study's results show that test images have a 91% accuracy rate, while training images have a 95% accuracy rate.



Literature Review

Additionally, other open-access studies have explored CNN-based approaches for skin lesion classification using various datasets and architectures. These studies consistently demonstrate the effectiveness of deep learning for visual diagnosis but also reveal common limitations, including reliance on image data alone, lack of interpretability, and absence of integrated medical knowledge systems.

Convolutional Neural Network-Based Approach For Skin Lesion Classification

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Abstract

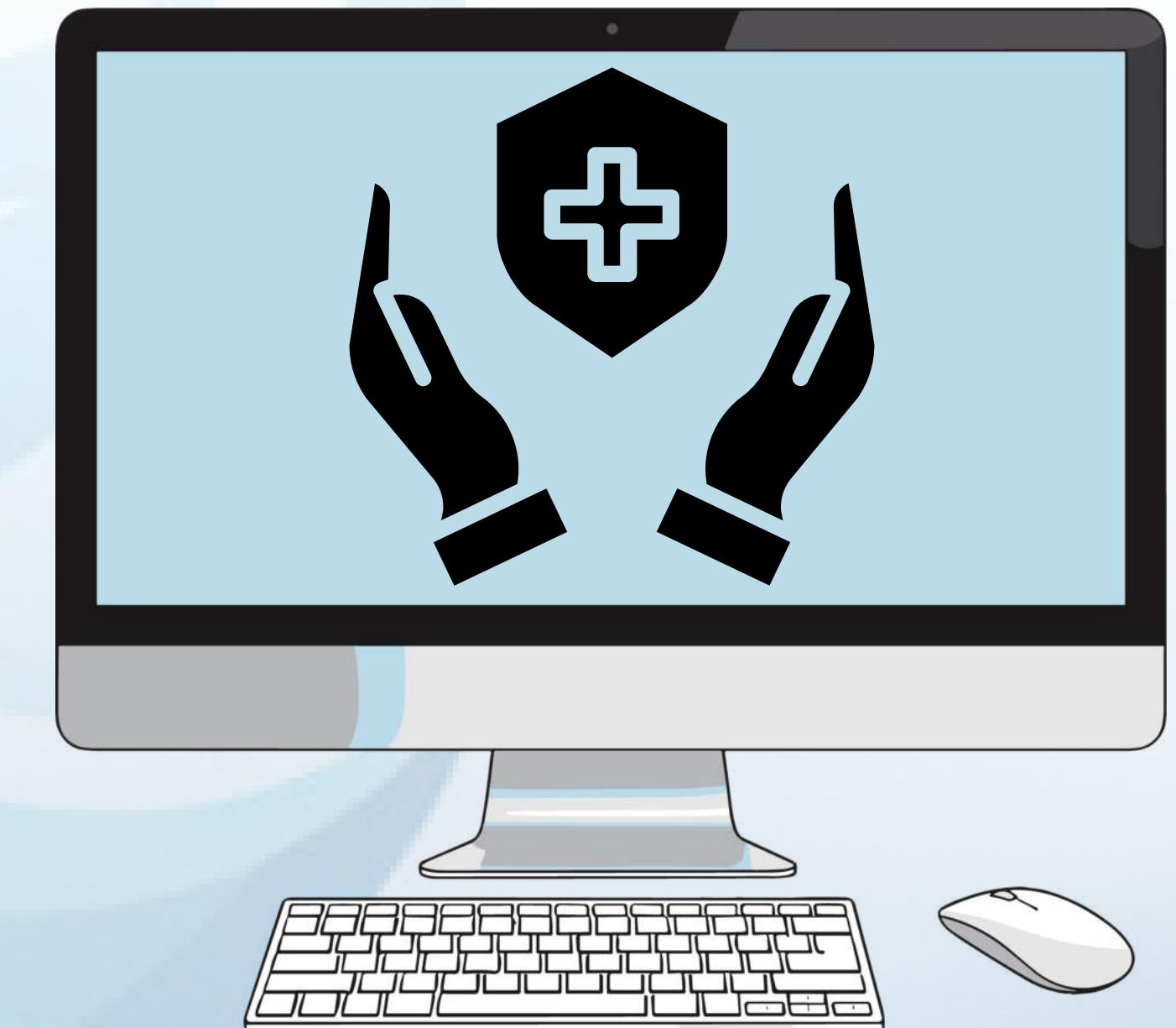
Skin cancer represents one of the primary forms of cancer arising from various dermatological disorders. It can be further categorized based on morphological characteristics, coloration, structure, and texture. Given the rising incidence of skin cancer, its significant mortality rates, and the substantial costs associated with medical treatment, the imperative lies in early detection to promptly diagnose symptoms and initiate appropriate interventions. Traditionally, skin cancer diagnosis and detection involve manual screening and visual examination conducted by dermatologists. These techniques are complex, error-prone, and time-consuming. Machine learning algorithms, particularly deep learning approaches, have been applied to analyze images of skin lesions, detect potential cancerous growths, and provide predictions regarding the likelihood of malignancy. In this paper, we have developed an optimized deep convolutional neural network (DCNN) specifically tailored for classifying skin lesions into benign and malignant categories. Thereby, enhancing the precision of disease diagnosis. Our study encompassed the utilization of a dataset comprising 3,297 dermoscopic images. To enhance the model's performance, we applied rigorous data preprocessing techniques and softmax activation algorithms. The suggested approach employs multiple optimizers, including Adam, RMSProp, and SGD, all configured with a learning rate of 0.0001. The outcomes of our experiments reveal that the Adam optimizer outperforms the others in distinguishing benign and malignant skin lesions within the ISIC dataset, boasting an accuracy score of 84 %, a loss rate of 32 %, a recall rating of 85 %, a precision score of 85 %, a f1-score of 85 %, and a ROC-AUC of 83 %.



Literature Review



Based on the reviewed literature published after 2021, it is evident that deep learning has become the dominant approach for automated skin disease classification. While existing systems achieve high accuracy in disease detection, they largely function as standalone diagnostic tools. The integration of structured medical knowledge, treatment recommendations, drug interactions, and contraindications remains largely unexplored. This identified research gap directly motivates the proposed system, which aims to combine deep learning-based skin disease classification with a medical knowledge base to enhance clinical reliability and patient safety.





Literature Review

Existing Web-Based Dermatology Platforms :

ModelDerm: A web-based AI dermatology platform that provides image-based skin condition analysis with general informational support, without treatment or medication management.

First Derm: An online AI-assisted system that analyzes skin images by retrieving visually similar dermatological cases for educational purposes rather than direct diagnosis.

SkinScreen: A web-based tool focused primarily on skin cancer risk assessment using AI, encouraging users to seek professional medical consultation.

SkinDetect AI: An AI-powered online platform that performs image-based skin analysis mainly for skin cancer detection, with limited disease coverage and no integrated treatment support.

The screenshot shows the SkinDetect AI homepage with a dark background. At the top, it features the logo and the text "SkinDetect AI" and "AI-powered Online Skin Disease Analysis Tool". Below this, it claims "Accurately Identifies 49 Types of Skin Problems". It has three buttons: "Free Diagnosis", "Powered by Visual AI", and "Professional Diagnostic Model". In the center, there is a dashed box with a camera icon and the text "Click to upload the skin disease image".

The screenshot shows the First Derm website. It has a header "FIRST DERM" and a "Get checked" button. Below is a section with a camera icon and the text "Press here to add/take a photo". There is also a checkbox for "Check this box to indicate you have read and agree with our Terms & Conditions" and an "Analyze" button.

The screenshot shows the SkinScreen website. At the top, it has a navigation bar with "Home", "Products", "News & Blog", "FAQs", "API", "Contact Us", and "About". Below this, it says "SkinScreen User Process" with four steps: "Take picture of skin lesion", "Browse for image through the web application", "Receive your risk results in real-time", and "Schedule a dermatology consultation based on risk results". It shows two skin lesion images. Under "Risk Results", it lists: 1. Melanoma (malignant): 85.9%, 2. Dermatofibroma (benign): 8.0%, 3. Benign Keratosis (benign): 6.1%. The bottom part shows a form for providing additional information about the lesion, including gender (Male), age (1928), onset (Within a Week), symptoms (-itching-), and severity (Mild-Moderate). It also shows a preview of a skin lesion image and a "Submit" button.

To better highlight the limitations of existing web-based dermatology systems and motivate the proposed solution, Table X presents a comparative analysis between current platforms and the proposed Skinova system.



Literature Review

Comparative Analysis of Web-Based AI Dermatology Platforms

| Feature / Aspect | ModelDerm | First Derm | SkinScreen | SkinDetect AI | Skinova (Proposed System) |
|--------------------------------------|-----------------------|------------|--------------------|-----------------------|--|
| Platform Type | Web-based | Web-based | Web-based | Web-based | Web-based |
| Number of Diagnosed Diseases | Limited / unspecified | Limited | Mainly skin cancer | Mostly cancer-related | 35 different skin diseases |
| Diagnosis + Treatment Recommendation | ✗ | ✗ | ✗ | ✗ | Full diagnosis with treatment guidance |
| Medication Reminder System | ✗ | ✗ | ✗ | ✗ | ✓ |
| Drug-Drug Interaction Detection | ✗ | ✗ | ✗ | ✗ | ✓ |
| Nearest Clinic via Maps | ✗ | ✗ | ✗ | ✗ | ✓ |
| Nearest Pharmacy Locator | ✗ | ✗ | ✗ | ✗ | ✓ |
| Patient Community for Similar Cases | ✗ | ✗ | ✗ | ✗ | ✓ |
| Medical History Export / Printing | ✗ | ✗ | ✗ | ✗ | ✓ |
| Explainability of AI Results | ✗ | ✗ | ✗ | ✗ | ✓ |



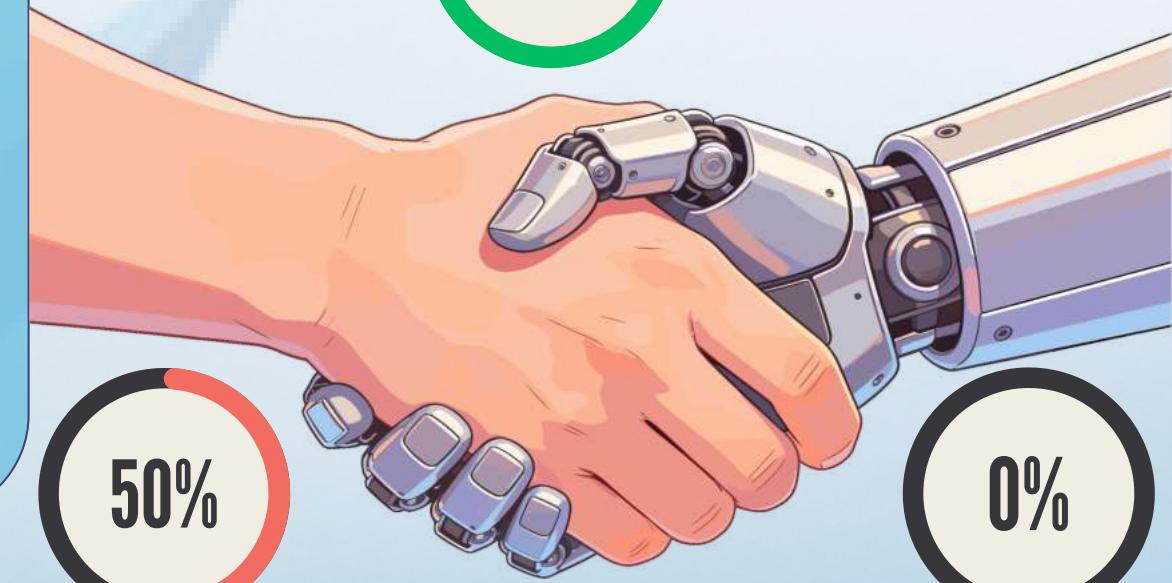
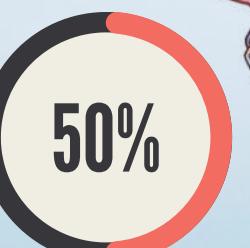
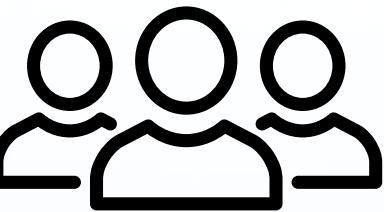
Problem Statement

Skin diseases are among the most common health problems worldwide, making early and accurate diagnosis essential to prevent serious complications.

However, access to dermatological care is often limited due to high costs, specialist shortages, and geographical barriers.

Another major limitation is the lack of integration between AI-based diagnosis and medical decision support, as most systems only predict the disease without addressing treatment safety, contraindications, or drug-drug interactions. This gap can expose patients to unsafe or inappropriate treatments, especially in complex medical cases.

Additionally, existing dermatology applications often function as black-box systems, providing limited transparency and interpretability. Users receive a predicted diagnosis without understanding the reasoning behind the decision or the confidence level of the model. This lack of interpretability reduces user trust and limits the practical adoption of such systems in clinical environments



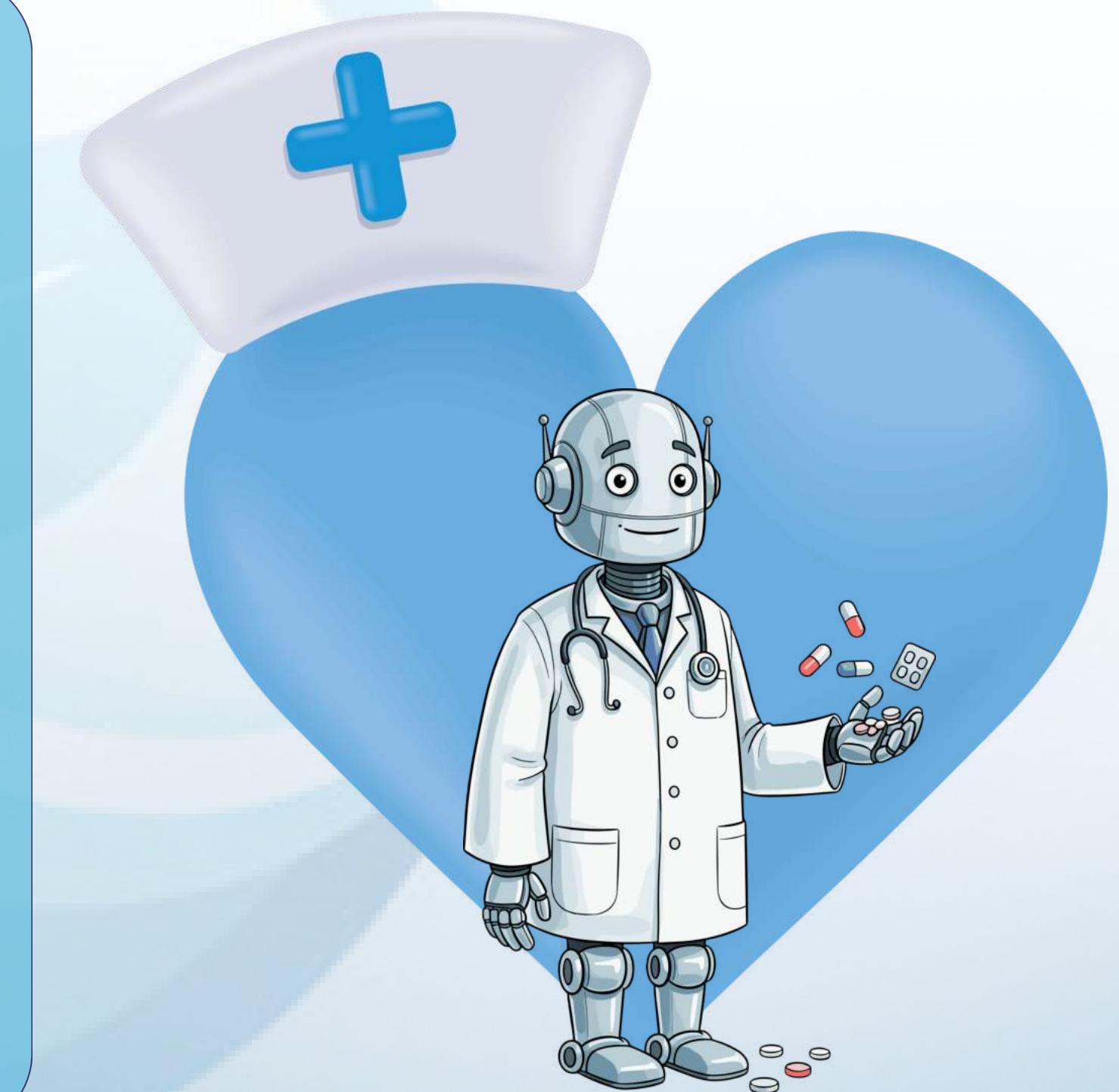


Problem Statement



Moreover, the majority of current systems do not support personalized medical recommendations. Patient-specific factors such as age, medical history, and current medications are rarely considered, even though they play a crucial role in determining safe and effective treatment plans. As a result, AI-based diagnostic tools remain insufficient for real-world healthcare deployment.

Therefore, the core problem addressed in this project can be summarized as follows: existing AI-based skin disease diagnosis systems provide high classification accuracy but fail to deliver clinically meaningful and safe decision support. There is a clear need for an intelligent system that not only classifies skin diseases accurately but also integrates structured medical knowledge to support treatment safety, handle drug interactions, and enhance overall clinical reliability.





Key Features

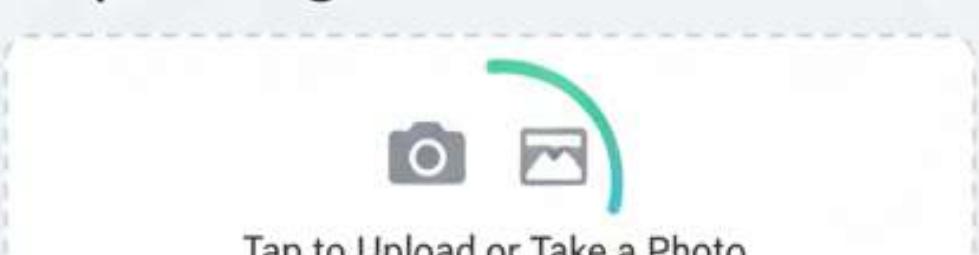
The proposed system is an intelligent, AI-driven platform designed to assist in the early detection, management, and awareness of skin diseases. It integrates deep learning, medical knowledge, user interaction, and location-based services to provide a comprehensive dermatological support solution.

Upload & Diagnose

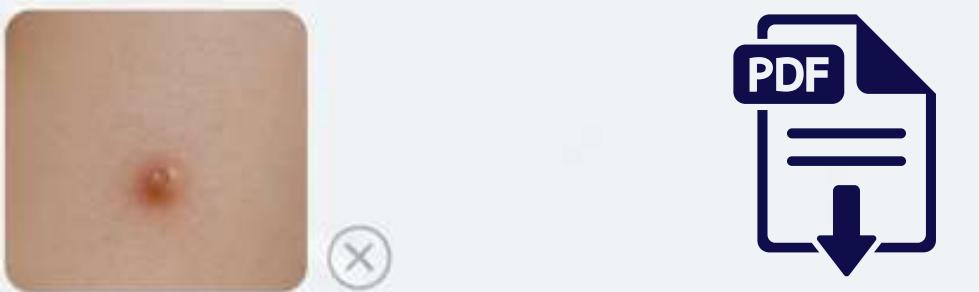
The system enables users to upload images of skin conditions directly through the platform. After image submission, a deep learning-based classification model analyzes the image and predicts the most probable skin disease. The diagnosis process is fully automated and provides fast and accurate results along with confidence scores, enhancing transparency and reliability. Furthermore, the system empowers patients by providing the option to generate, download, and print a comprehensive diagnostic report in PDF format for further medical consultation.

Upload & Diagnose Skin Lesion

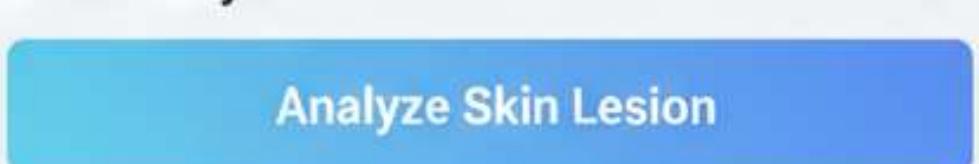
1. Upload Image



Tap to Upload or Take a Photo



2. AI Analysis



Preliminary Results
Diagnosis: Benign Nevus
(Common Mole)
92.5% Certainty



Key Features

Smart Medication Safety Check

Before receiving treatment recommendations, users are required to select their currently used medications from a predefined list.

After the disease is diagnosed, the system cross-checks the recommended treatment against the user's selected medications.

This process is powered by a manually constructed medical knowledge dataset created specifically for this project.

The dataset includes information about skin diseases, standard treatments, drug-drug interactions, contraindications, and safe alternatives.

If no interaction is detected, the system confirms that the treatment is safe.

In case of a detected conflict, the system automatically provides a medically safe alternative, ensuring patient safety and minimizing health risks.

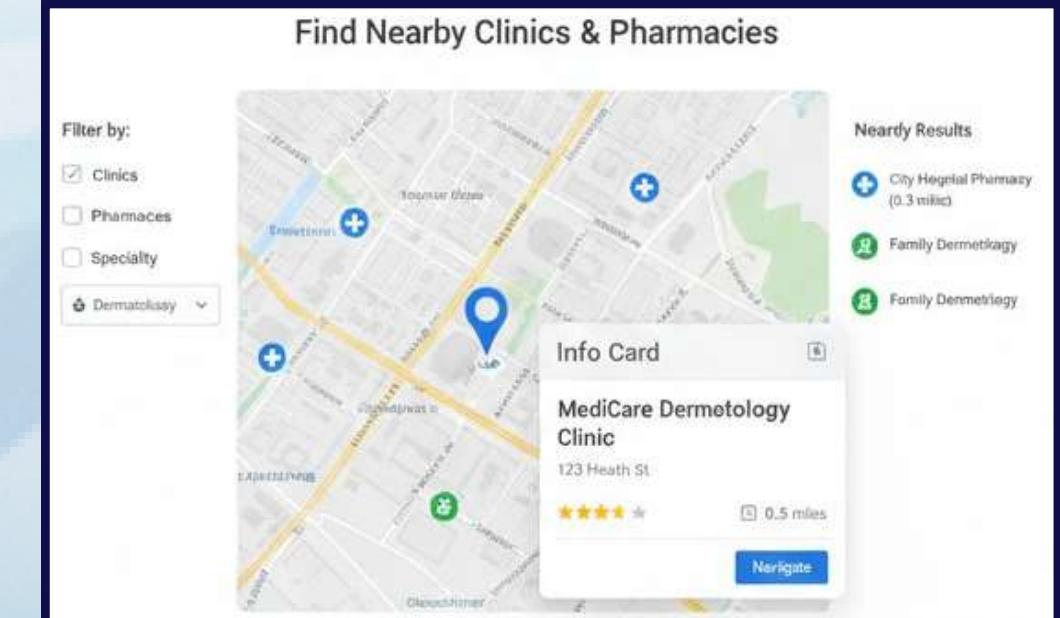


Clinics & Pharmacies – Nearest Maps

The system integrates map-based location services to help users find the nearest dermatology clinics and pharmacies.

This feature improves accessibility to professional healthcare services and facilitates timely medical consultation when required.

Find Nearby Clinics & Pharmacies

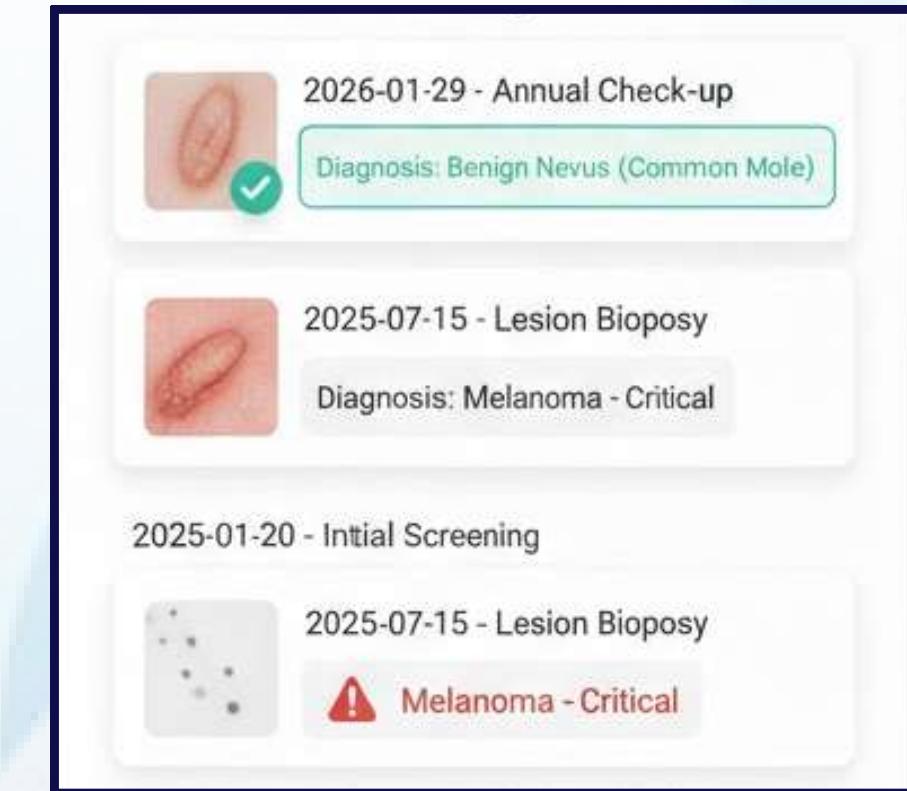




Key Features

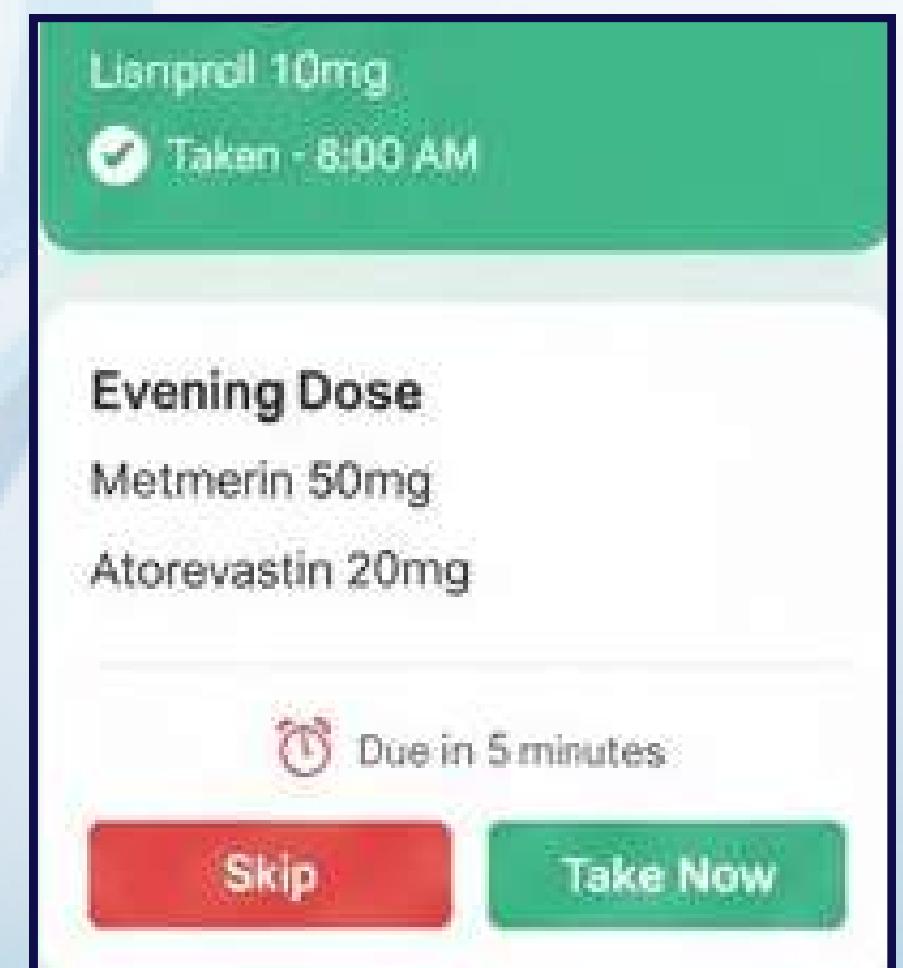
Medical History Management

The system allows users to store and manage their medical history, including previous diagnoses and relevant health information. Maintaining medical history enables more informed recommendations and supports continuity of care over time.



Medication Reminder

To support treatment adherence, the system provides a medication reminder feature that helps users follow prescribed treatment schedules. This reduces the risk of missed doses and improves overall treatment effectiveness.





Key Features

Community – Similar Cases

The platform includes a community feature that allows users to explore anonymized cases similar to their condition. By viewing experiences, treatments, and outcomes of similar cases, users can gain insights and psychological support, promoting knowledge sharing and engagement.

Eczema Support (234 members)

Dr. Sarah Johnson (Dermatologist) 2 days ago: Weekly Tip: Always apply sunscreen 15-30 minutes before sun exposure for maximum protection.

Emily Rose 2 hours ago: Just tried the new moisturizer routine suggested by Dr. Sarah. Seeing improvements already! 🌟 12 likes, 3 comments

Mike Chen 5 hours ago: Has anyone tried phototherapy? My dermatologist suggested it for my eczema. 8 likes, 7 comments

Sarah K. 1 day ago: Progress update: 3 months into treatment! Here's my journey so far. 24 likes, 15 comments

James Wilson 1 day ago: [Image placeholder]

Awareness & Education

An awareness section is included to educate users about skin diseases, early symptoms, prevention methods, and safe medical practices. This feature promotes proactive healthcare behavior and increases public awareness of dermatological conditions.

Spot Skin Cancer Early!
Knowledge for a Healthier You

Interactive Tools: Learn More, Skin Self-Check Quiz, Symptom Checker

Educational Topics:

- Melanomas: The ABCEs
- Common Skin Conditions
- Common Skin Conditions
- Sun Protection & Prevention

Latest Articles:

- The Science of SPF
- Diet for Healthy Skin
- Myths About Acne



System Requirements



Functional Requirements

- The system shall allow users to register and log in securely.
- The user shall be able to upload a skin image for disease detection.
- The system shall analyze the uploaded image using an AI model to detect possible skin diseases.
- The system shall check for drug interactions based on the user's medications and medical history.
- If a conflict is detected, the system shall suggest safe alternative drugs.
- The system shall notify users about their medicine schedule (e.g., reminder notifications).
- The system shall display results of disease detection and drug interaction clearly to the user.
- The system shall allow users to join a community group to communicate with other patients who have the same condition.
- The system shall store and update the patient's data securely in the database.

Non-Functional Requirements

- The system shall provide results within few seconds of image upload.
- The system shall be secure, protecting user data and medical information.
- The system shall have a user-friendly interface that is easy to navigate.
- The system shall support multiple users at the same time without performance issues.
- The system shall be designed for easy maintenance and future updates.
- The system should support future expansion, such as adding new diseases or enhancing AI models.



System Requirements



Hardware Requirements

A system equipped with a modern multi-core processor is required for model training and evaluation. A GPU-enabled environment is recommended to accelerate deep learning training and inference processes. At least 8 GB of RAM is required, with higher memory recommended for training large convolutional neural networks. Sufficient storage is required to store datasets, trained models, and medical knowledge files.

Software Requirements

The system requires a Python-based development environment. Deep learning frameworks such as TensorFlow and Keras are required for model training and inference. Supporting libraries for data processing, visualization, and evaluation are required. A Jupyter Notebook environment is used for experimentation and model development. A suitable database system is required to store medical history and medication data. A web or graphical user interface framework is required to enable user interaction.

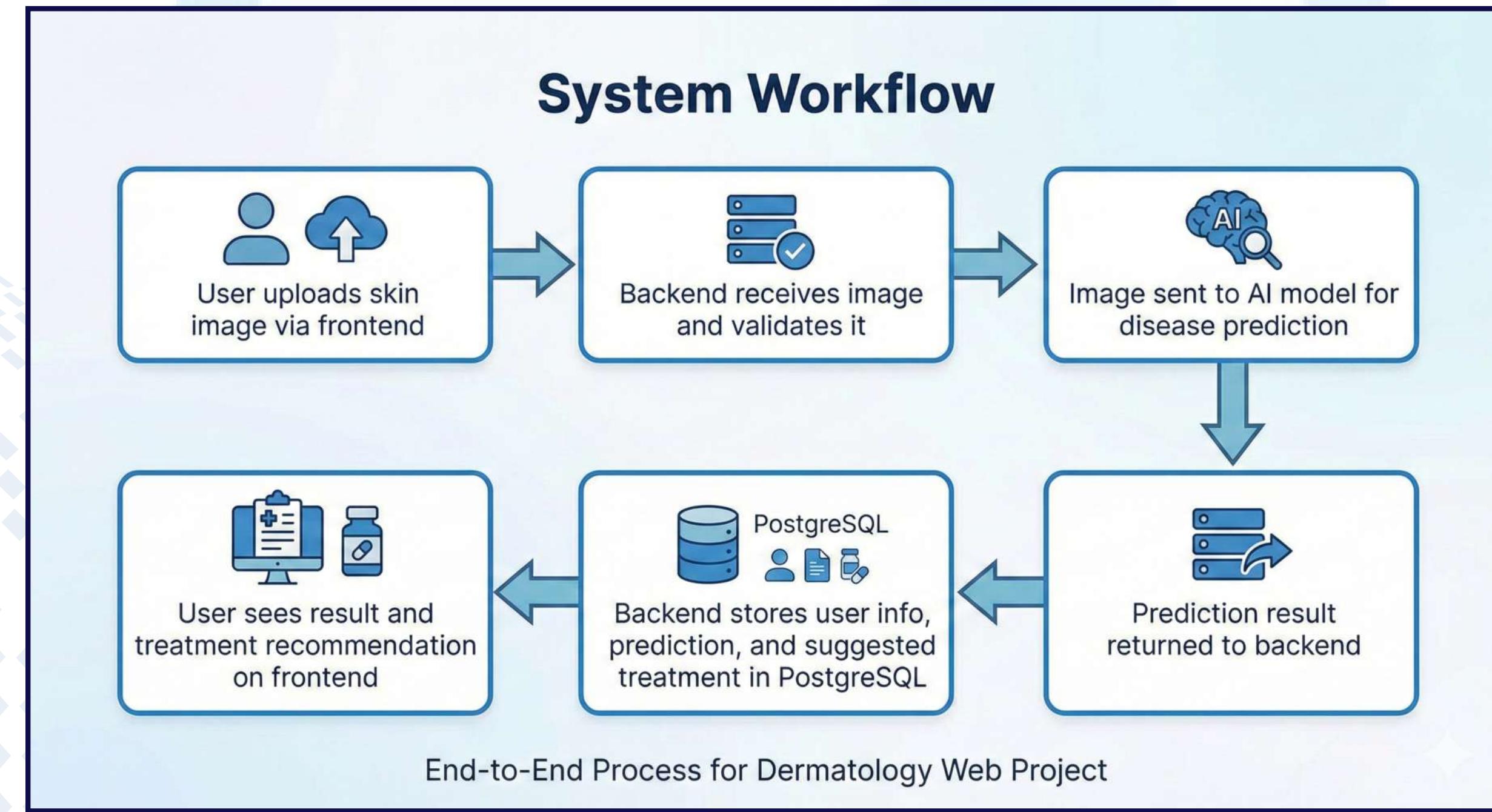
Dataset Requirements

The system requires a labeled skin disease image dataset for model training and evaluation. The system uses a custom manually created medical knowledge dataset containing diseases, medications, interactions, contraindications, and safe alternatives. All datasets must be preprocessed, cleaned, and validated to ensure data consistency and reliability.

Methodology



System Workflow :





Methodology



The methodology of this project is designed based on a comparative experimental framework, where multiple deep learning models were developed, evaluated, and analyzed to identify the most effective approach for skin disease classification. The methodology follows a data-driven and evidence-based process, ensuring that the final system selection is justified by quantitative results

Experimental Design Overview

The project follows a multi-model experimental methodology consisting of three main stages:

1. Development of multiple deep learning models using different architectures.
2. Independent training and evaluation of each model on its corresponding dataset.
3. Comparative analysis of model performance to select the final deployment model.

This approach ensures that the final system is not chosen arbitrarily but is supported by experimental evidence and performance metrics.



Methodology



► Data Collection and Preparation (from Kaggle) :

Three different datasets were used to evaluate the performance of various model architectures:

HAM10000 Dataset:

Used with a custom CNN architecture to classify seven types of skin lesions. This dataset is known for its real-world imbalance and clinical relevance.

Skin Disease Image Dataset:

Used with a ResNet50 transfer learning model to classify ten dermatological conditions.

Massive Skin Disease Balanced Dataset:

Used with the ConvNeXt architecture to classify thirty-five distinct skin diseases. This dataset is strictly balanced to eliminate bias toward dominant classes. Each dataset was analyzed, cleaned, and prepared independently to match the input requirements of the corresponding model.



Methodology



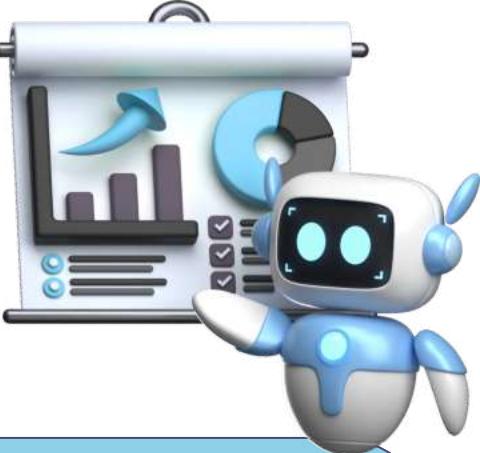
Data Preprocessing and Augmentation

To ensure consistency and optimal model performance, preprocessing techniques were applied as follows:

- Images were resized according to the architectural requirements of each model:
 - 28×28 pixels for the custom CNN.
 - 224×224 pixels for ResNet50.
 - 150×150 pixels for ConvNeXt.
- Pixel normalization was applied to stabilize training and accelerate convergence.
- Advanced data augmentation techniques were employed, including rotation, flipping, cropping, affine transformations, and color jittering. These techniques improve generalization by simulating real-world variations in skin image acquisition.
- For the HAM10000 dataset, class imbalance was addressed using oversampling techniques to ensure fair representation of rare but critical diseases such as melanoma



Methodology



Model Architectures

Custom CNN Model (HAM10000)

A sequential convolutional neural network was developed using multiple convolutional layers, max-pooling layers, and dropout for regularization. The model was optimized using the Adam optimizer and categorical cross-entropy loss function. This model served as a baseline to evaluate the effectiveness of traditional CNN architectures.

ResNet50 Transfer Learning Model

A pre-trained ResNet50 architecture was employed using transfer learning. The backbone was initialized with ImageNet weights, and the classification head was redesigned using Global Average Pooling, batch normalization, and fully connected layers.

Fine-tuning was applied by unfreezing the last layers of the network to adapt feature extraction specifically to dermatological patterns. Learning rate scheduling was used to stabilize training and improve convergence.

ConvNeXt Model

The ConvNeXt architecture was selected as a state-of-the-art model combining CNN efficiency with transformer-inspired design principles. The model was trained on a large, balanced dataset to ensure objective performance across all disease classes.

Advanced augmentation, iterative fine-tuning, and hyperparameter optimization were applied to capture subtle morphological differences between skin diseases.



Methodology



Training Strategy

All models were trained using supervised learning with labeled image data. Training processes were monitored using accuracy and loss curves to detect overfitting and ensure stable learning behavior.

Validation strategies were applied to evaluate generalization performance, and hyperparameters such as learning rate, dropout rate, and training epochs were adjusted accordingly.

Performance Evaluation

Each model was evaluated using standard classification metrics:

- Accuracy
- Precision
- Recall
- F1-score

The evaluation results demonstrated clear performance differences between the models:

- The ResNet50 model achieved **93.3% accuracy**.
- The custom CNN achieved approximately **97.32% accuracy**.
- The ConvNeXt model achieved the highest performance with **98.53% accuracy**.

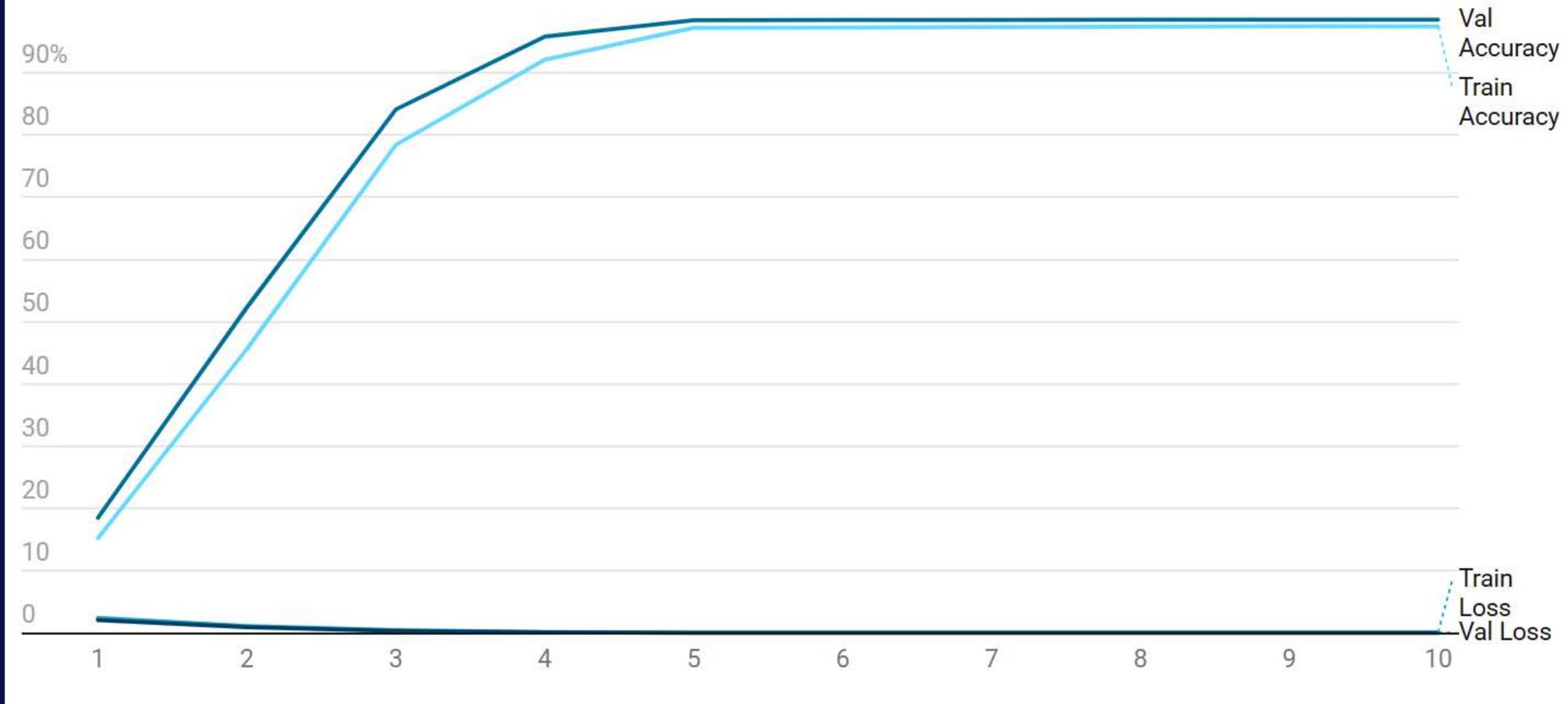


Methodology

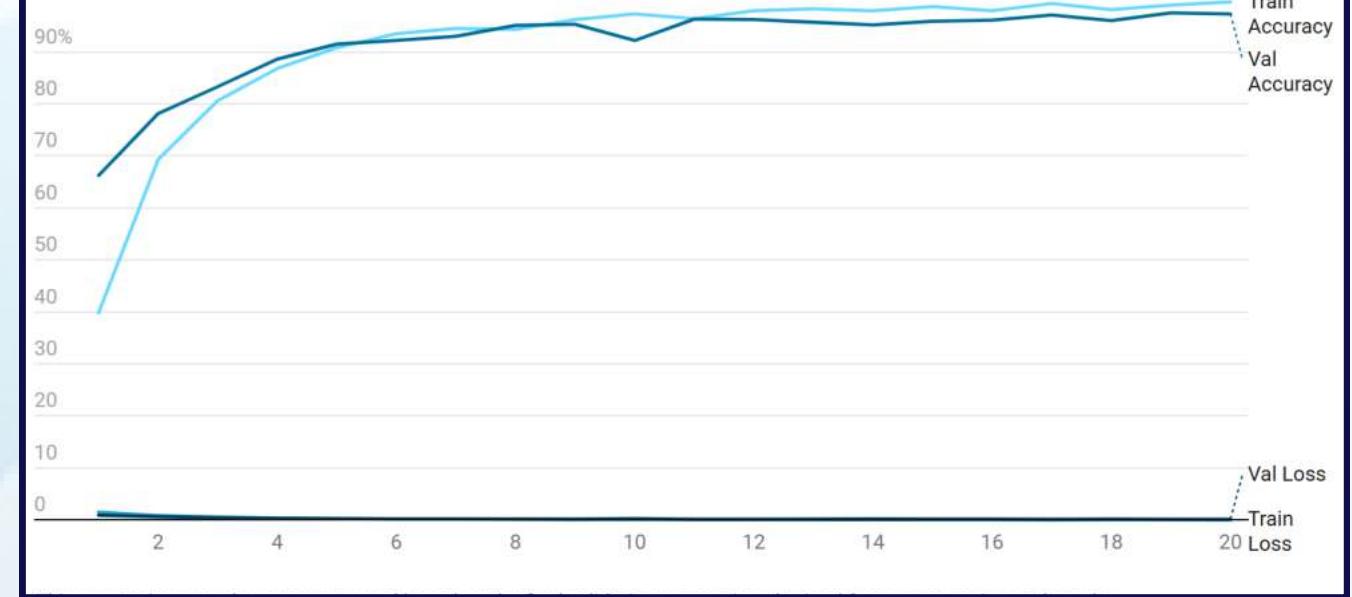


➤ A graph showing the results during training for each model :

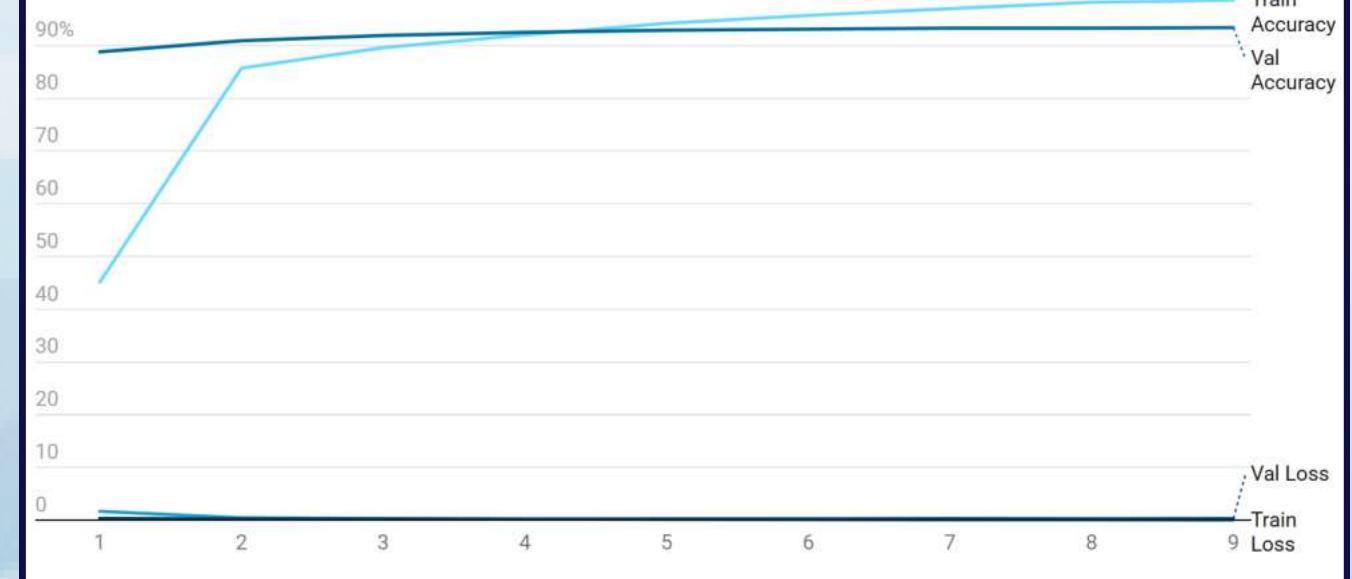
Massive-skin-disease-balanced-dataset: ConvexNet



HAM-10000:CNN



Skin-disease-images: ResNet50





Methodology



➤ Visualization comparison illustrates the differences between Accuracy for each model :

Model Comparison

■ Accuracy

massive-skin-disease-balanced-dataset:ConvexNet

98%

HAM-10000:CNN

97%

Skin-disease-images:ResNet50

93%

Methodology



➤ Comparison table between three models to choose the most suitable one :

| Comparative Criteria | Model I: ConvNeXt | Model II: Custom CNN | Model III: ResNet50 |
|----------------------|-------------------------------|-------------------------|-------------------------------|
| Architecture | ConvNeXt (Base) | Sequential Custom CNN | ResNet50 (Residual) |
| Dataset | Massive Skin Balanced | HAM10000 | Skin Diseases Image Dataset |
| Classification Scale | 35 Disease Categories | 7 Disease Categories | 10 Disease Categories |
| Methodology | Modern Fine-Tuning | Training from Scratch | Standard Transfer Learning |
| Core Technique | Modern Hybrid Blocks | Random Oversampling | Identity Shortcut Connections |
| Input Resolution | 150×150 pixels | 28×28 pixels | 224×224 pixels |
| Overall Accuracy | 98.53% | 97.32% | 93.3% |
| Clinical Strength | High Scalability (35 Classes) | Data Imbalance Handling | 99% Melanoma Recall |

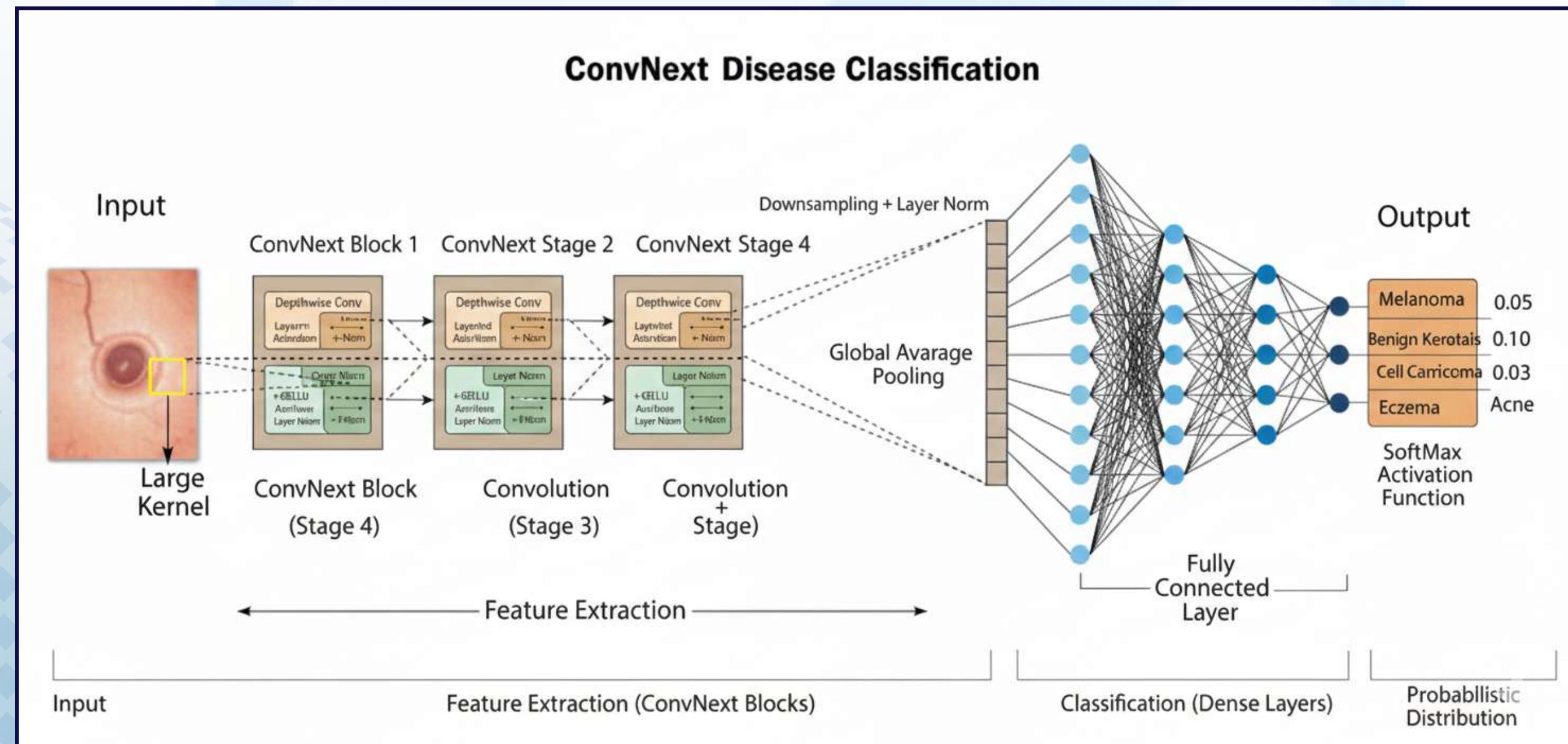


Methodology



Final Model Selection

Based on the comparative evaluation, the ConvNeXt model was selected as the final system model due to its superior accuracy, balanced performance across all classes, and robustness against dataset bias. This model was integrated as the core diagnostic engine of the system.





Methodology



The dataset we used in the best ConvNeXt model and a sample of it :

This dataset contains 262,874 images of various skin conditions, categorized into 35 different disease classes. It is designed for deep learning-based image classification and can be used to train models for automatic dermatology diagnosis.

Disease Categories (35 Classes)

The dataset includes images of various skin conditions, including but not limited to:

Acne & Rosacea

Actinic Keratosis & Malignant Lesions

Atopic Dermatitis

Eczema

Melanoma & Moles

Psoriasis & Lichen Planus

Fungal Infections (Ringworm, Athlete's Foot, Nail Fungus)

Herpes, HPV, & STDs

Viral Infections (Chickenpox, Shingles, Warts, Molluscum)

Bacterial Infections (Cellulitis, Impetigo)

Lupus & Connective Tissue Diseases

Pigmentation Disorders

Systemic Diseases with Skin Manifestations



Urticaria Hives



Basal Impetigo



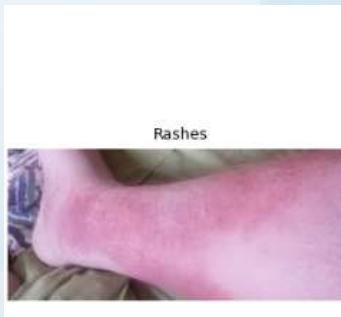
Healthy



Vascular Tumors Poison Ivy Photos And Other Contact Dermatitis Fu Ringworm



Fu Nail Fungus



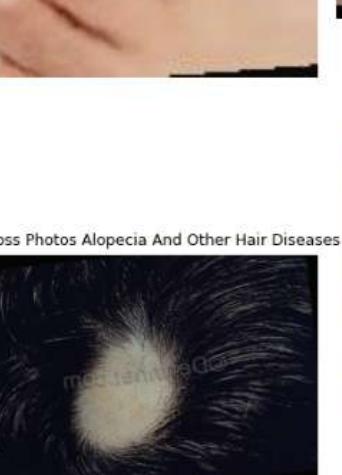
Rashes



Cellulitis Impetigo And Other Bacterial Infections



Warts Molluscum And Other Viral Infections Hair Loss Photos Alopecia And Other Hair Diseases



Eczema Photos



Methodology

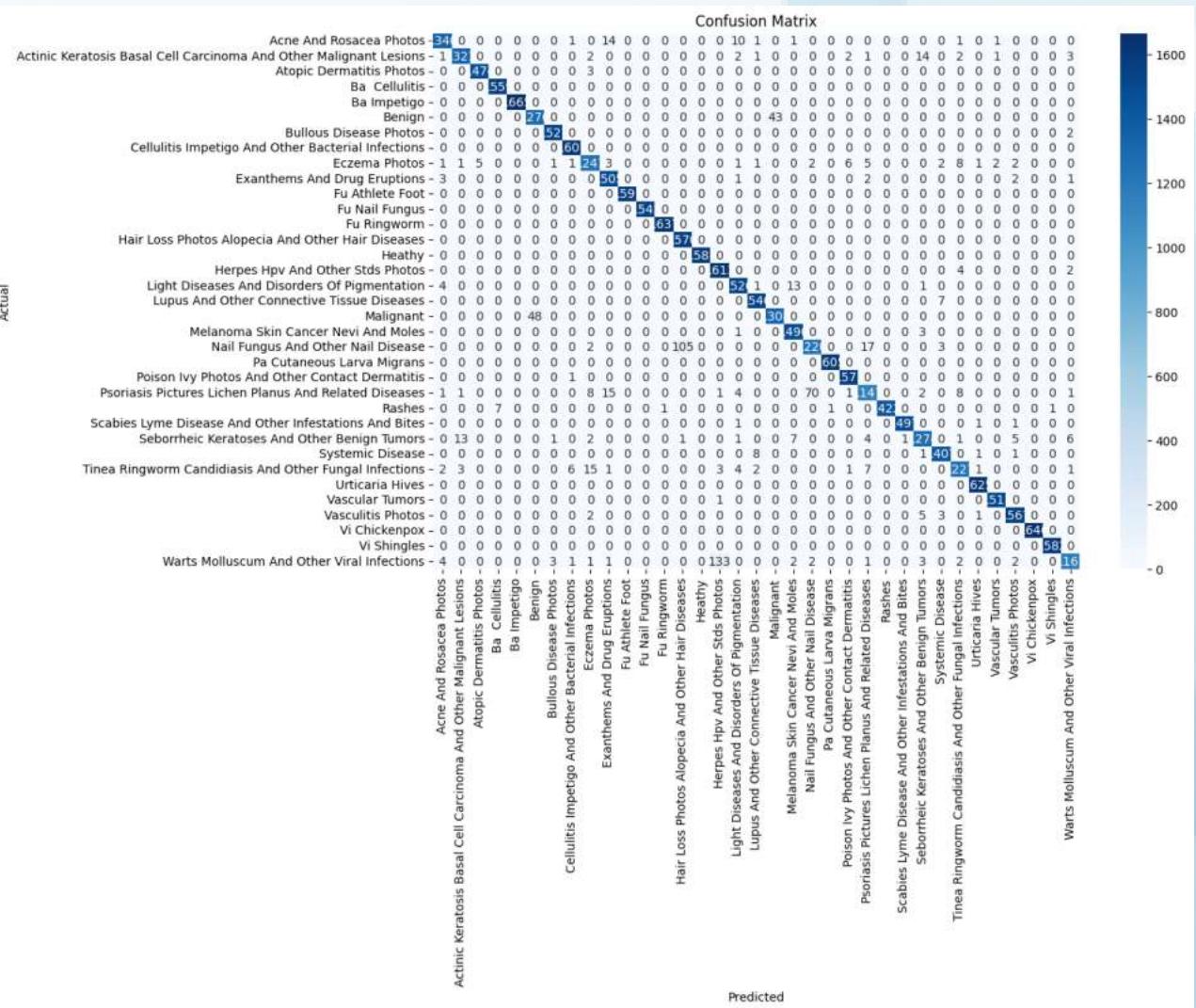


Classification Report Results :

Precision & Recall :

F1-score & Support :

Confusion Matrix :

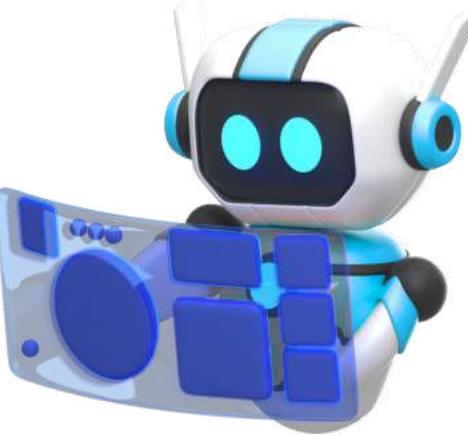


| Classification Report: | | precision | recall |
|--|--|-----------|----------|
| Acne And Rosacea Photos | | 0.988201 | 0.978817 |
| Actinic Keratosis Basal Cell Carcinoma And Other Skin Lesions Photos | | 0.986557 | 0.978519 |
| Atopic Dermatitis Photos | | 0.996619 | 0.997969 |
| Bacterial Cellulitis Photos | | 0.995530 | 1.000000 |
| Bacterial Impetigo Photos | | 1.000000 | 1.000000 |
| Benign | | 0.963746 | 0.967400 |
| Bullous Disease Photos | | 0.996736 | 0.998692 |
| Cellulitis Impetigo And Other Bacterial Infections Photos | | 0.993816 | 1.000000 |
| Eczema Photos | | 0.972571 | 0.967264 |
| Exanthems And Drug Eruptions Photos | | 0.977908 | 0.994055 |
| Fungal Athlete Foot Photos | | 1.000000 | 1.000000 |
| Fungal Nail Fungus Photos | | 1.000000 | 1.000000 |
| Fungal Ringworm Photos | | 0.999389 | 1.000000 |
| Hair Loss Photos Alopecia And Other Hair Diseases Photos | | 0.936754 | 1.000000 |
| Healthy | | 1.000000 | 1.000000 |
| Herpes HpV And Other STDs Photos | | 0.921188 | 0.996294 |
| Light Diseases And Disorders Of Pigmentation Photos | | 0.983881 | 0.987702 |
| Lupus And Other Connective Tissue Diseases Photos | | 0.991026 | 0.995493 |
| Malignant | | 0.968172 | 0.964602 |
| Melanoma Skin Cancer Nevi And Moles Photos | | 0.984798 | 0.997323 |
| Nail Fungus And Other Nail Disease Photos | | 0.942813 | 0.905716 |
| Parasitic Cutaneous Larva Migrans Photos | | 0.999377 | 1.000000 |
| Poison Ivy Photos And Other Contact Dermatitis Photos | | 0.993691 | 0.999365 |
| Psoriasis Pictures Lichen Planus And Related Diseases Photos | | 0.968750 | 0.911041 |
| Rashes | | 1.000000 | 0.993017 |
| Scabies Lyme Disease And Other Infestations And Parasites Photos | | 0.999332 | 0.998000 |
| Seborrheic Keratoses And Other Benign Tumors Photos | | 0.977744 | 0.968085 |
| Systemic Disease Photos | | 0.989451 | 0.992243 |
| Tinea Ringworm Candidiasis And Other Fungal Infections Photos | | 0.979250 | 0.963865 |
| Urticaria Hives Photos | | 0.996933 | 1.000000 |
| Vascular Tumors Photos | | 0.997360 | 0.999339 |
| Vasculitis Photos | | 0.991772 | 0.993029 |
| Viral Chickenpox Photos | | 1.000000 | 1.000000 |
| Viral Shingles Photos | | 0.999368 | 1.000000 |
| Warts Molluscum And Other Viral Infections Photos | | 0.986475 | 0.882753 |
| accuracy | | 0.985429 | 0.985429 |
| macro avg | | 0.985120 | 0.983731 |
| weighted avg | | 0.985620 | 0.985429 |

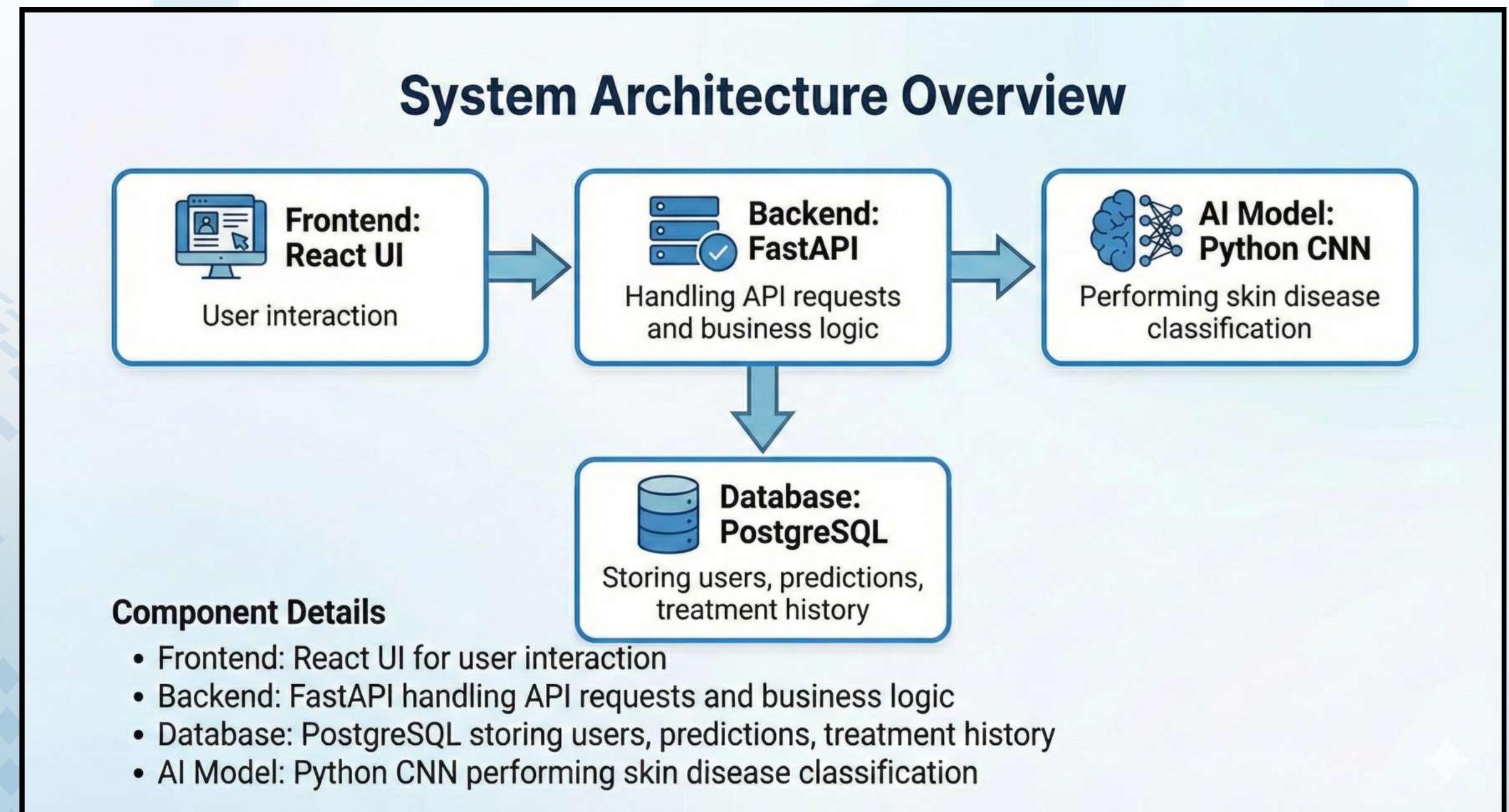
| | f1-score | support |
|--|----------|--------------|
| Acne And Rosacea Photos | 0.983486 | 1369.000000 |
| Actinic Keratosis Basal Cell Carcinoma And Other Skin Cancers Photos | 0.982521 | 1350.000000 |
| Atopic Dermatitis Photos | 0.997294 | 1477.000000 |
| Bacterial Cellulitis | 0.997760 | 1559.000000 |
| Bacterial Impetigo | 1.000000 | 1665.000000 |
| Benign | 0.965569 | 1319.000000 |
| Bullous Disease Photos | 0.997713 | 1529.000000 |
| Cellulitis Impetigo And Other Bacterial Infections | 0.996898 | 1607.000000 |
| Eczema Photos | 0.969910 | 1283.000000 |
| Exanthems And Drug Eruptions | 0.985915 | 1514.000000 |
| Fungal Athlete Foot | 1.000000 | 1597.000000 |
| Fungal Nail Fungus | 1.000000 | 1545.000000 |
| Fungal Ringworm | 0.999695 | 1637.000000 |
| Hair Loss Photos Alopecia And Other Hair Diseases | 0.967344 | 1570.000000 |
| Healthy | 1.000000 | 1581.000000 |
| Herpes Hpv And Other Stds Photos | 0.957270 | 1619.000000 |
| Light Diseases And Disorders Of Pigmentation | 0.985788 | 1545.000000 |
| Lupus And Other Connective Tissue Diseases | 0.993254 | 1553.000000 |
| Malignant | 0.966383 | 1356.000000 |
| Melanoma Skin Cancer Nevi And Moles | 0.991021 | 1494.000000 |
| Nail Fungus And Other Nail Disease | 0.923892 | 1347.000000 |
| Parasitic Cutaneous Larva Migrans | 0.999689 | 1605.000000 |
| Poison Ivy Photos And Other Contact Dermatitis | 0.996520 | 1576.000000 |
| Psoriasis Pictures Lichen Planus And Related Diseases | 0.939009 | 1259.000000 |
| Rashes | 0.996496 | 1432.000000 |
| Scabies Lyme Disease And Other Infestations And Parasites | 0.998666 | 1500.000000 |
| Seborrheic Keratoses And Other Benign Tumors | 0.972890 | 1316.000000 |
| Systemic Disease | 0.990845 | 1418.000000 |
| Tinea Ringworm Candidiasis And Other Fungal Infections | 0.971496 | 1273.000000 |
| Urticaria Hives | 0.998464 | 1625.000000 |
| Vascular Tumors | 0.998348 | 1512.000000 |
| Vasculitis Photos | 0.992400 | 1578.000000 |
| Viral Chickenpox | 1.000000 | 1646.000000 |
| Viral Shingles | 0.999684 | 1582.000000 |
| Warts Molluscum And Other Viral Infections | 0.931737 | 1322.000000 |
| accuracy | 0.985429 | 0.985429 |
| macro avg | 0.984227 | 52160.000000 |
| weighted avg | 0.985336 | 52160.000000 |



Implementation

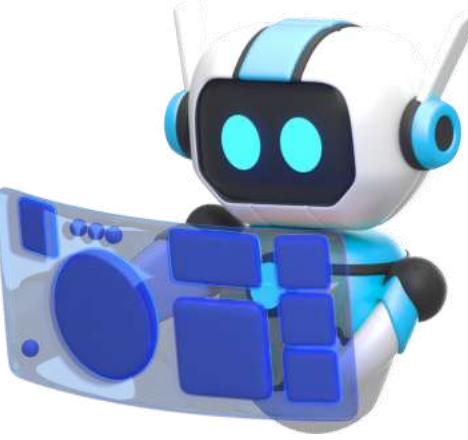


System Architecture :





Implementation



Layer Responsibilities

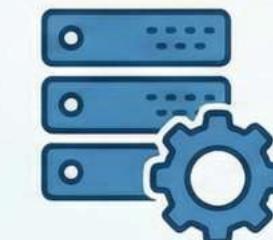
Implementation Details (High-Level)

Frontend



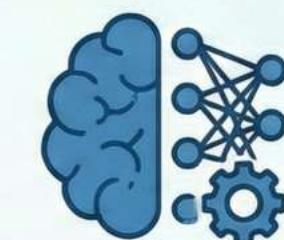
- Uploading images
- Displaying results
- Simple UI/UX

Backend



- API endpoints
- Business logic
- Security

AI Model



- Prediction
- Preprocessing
- Integration

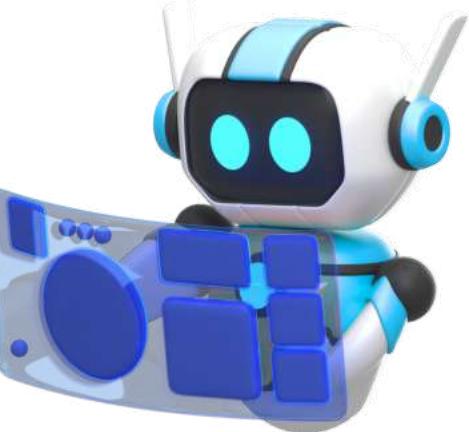
Database



- Storing and retrieving user and prediction data

High-Level Functional Responsibilities of System Components

Implementation



The implementation phase focuses on translating the proposed methodology into a fully functional system by integrating deep learning models with medical knowledge and user interaction workflows.

Deep Learning Model Implementation :

Multiple deep learning models were implemented using Python and TensorFlow/Keras. Each model was developed in a separate experimental environment to ensure isolated evaluation and fair comparison.

The final selected ConvNeXt model was trained using a balanced skin disease dataset and optimized through fine-tuning techniques. The trained model was then saved and prepared for inference, serving as the core diagnostic component of the system.

Medical Knowledge Base Implementation :

A custom medical knowledge base was implemented using a structured CSV dataset manually created by the project team. The dataset includes diseases, standard treatments, contraindications, drug-drug interactions, and safe alternatives. This dataset is loaded at runtime and queried dynamically during diagnosis to support medication safety verification.

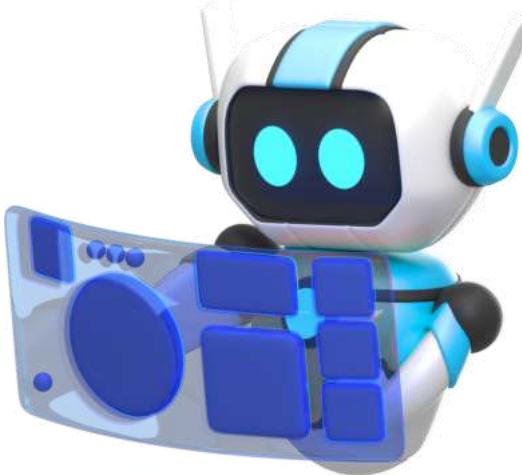
Medication Safety Logic :

After disease prediction, the system retrieves the recommended treatment from the medical knowledge base. The user's selected medications are then compared against known contraindications and interaction rules.

If no conflict is detected, the system confirms the treatment as safe. If a conflict is identified, the system automatically selects and recommends a safe alternative medication.



Implementation



The dataset we used in the Integrated Medical Safety Rules & Pharmacological Knowledge Base :

The dataset for Skinova's Clinical Decision Support System (CDSS) was manually curated by the author from multiple reputable sources, including DermNet and clinical guidelines.

It was designed to address the lack of existing datasets that simultaneously cover dermatological diseases, associated medications, adverse reactions, and safe alternatives.

This knowledge base includes 35 skin conditions with standard treatment protocols, supports automated detection of drug-drug interactions, identifies patient-specific contraindications, and dynamically recommends safe alternative therapies, ensuring patient-centered and clinically sound decision-making.

| Disease (AI Diagnosis) | Standard Treatment | Conflict / Contraindication | Safe Alternative |
|------------------------|--------------------------|--|---------------------|
| Acne & Rosacea | Doxycycline | Pregnancy (Contraindicated), Isotretinoin | Topical Combination |
| Bacterial Cellulitis | Amoxicillin-Clavulanate | Methotrexate (Risk of severe toxicity & liver damage) | Clindamycin (Oral) |
| Atopic Dermatitis | Systemic Corticosteroids | Insulin/Oral Hypoglycemics (Steroids can cause diabetes) | Tacrolimus Ointment |



Implementation



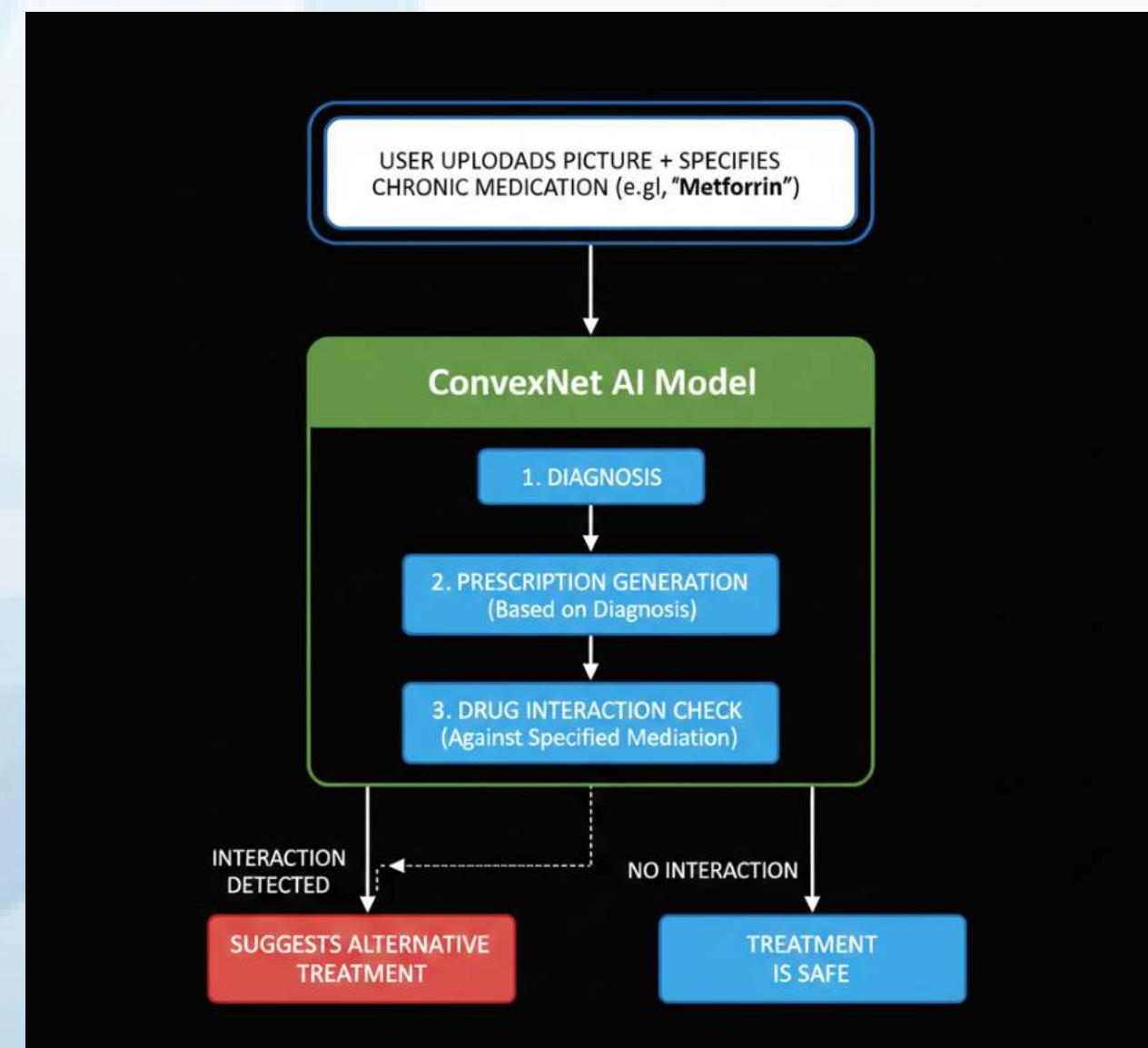
System Workflow Integration :

All components are integrated into a unified workflow. The system begins with image upload, followed by disease classification, medication selection, safety checking, and final recommendation output.

The implementation is modular, allowing independent updates to the model, medical dataset, or interface without affecting other system components.

Implementation Overview :

- CNN models implemented using TensorFlow/Keras
- ConvNeXt selected as final diagnostic model
- Custom medical knowledge base integrated
- Automated drug interaction and safety checking
- Modular system architecture



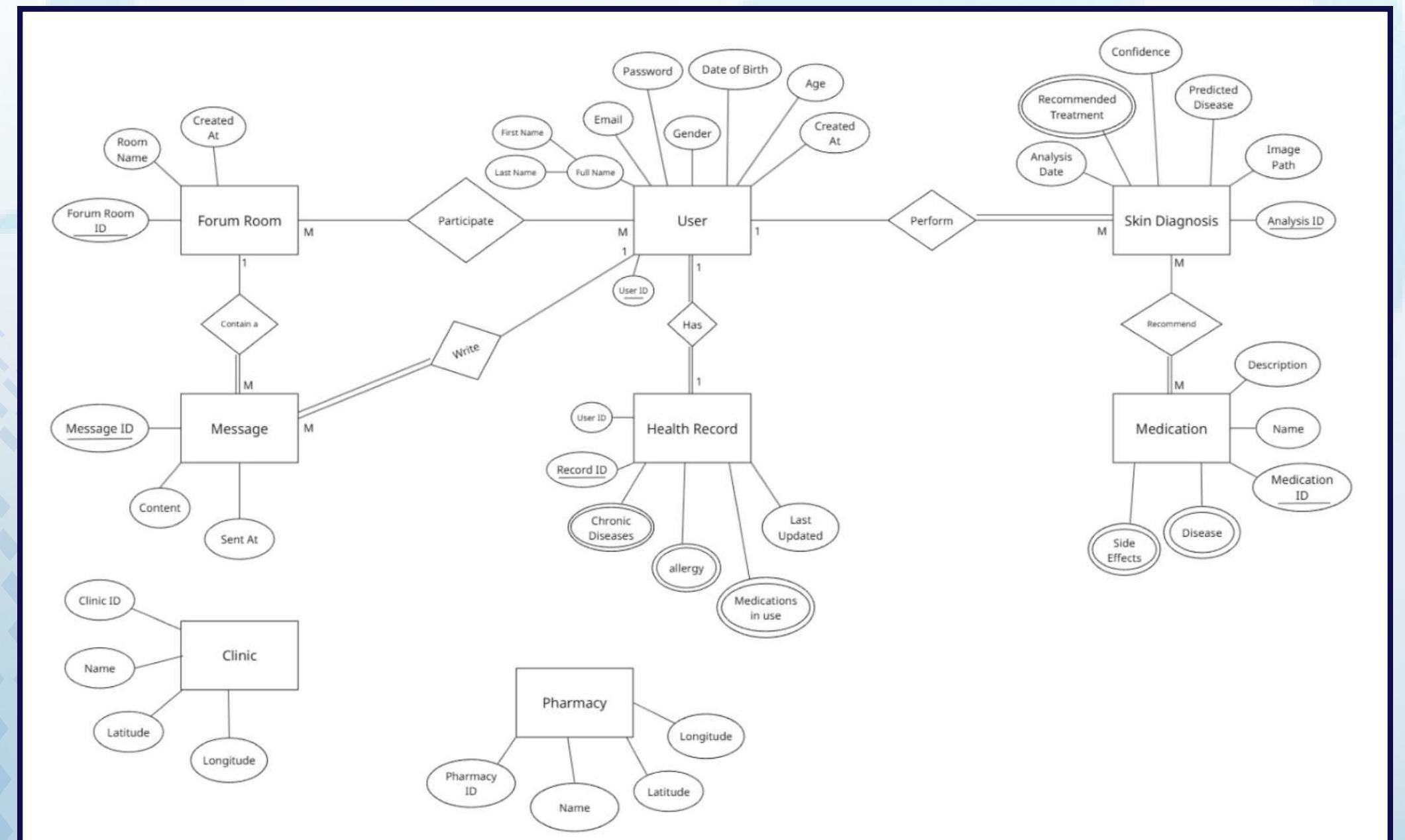


Implementation



Database Architecture / ERD :

The ERD diagram illustrates the structure of Skinova's database, showing entities, attributes, and relationships used to manage dermatological conditions, treatments, patient records, and safety rules.



Implementation

Demo of Skinova Model Functionality :

"This Python-based GUI prototype is used to test the Skinova AI model and visually display its prediction results before full frontend integration."

1. Chronic Medications (Select all that apply)

- Insulin
- Oral Hypoglycemics (e.g., Metformin)
- Warfarin/Anticoagulants
- Methotrexate
- Amiodarone (QT-prolonging drug)
- Statins (e.g., Simvastatin, Atorvastatin)
- Calcium-Channel Blockers (e.g., Amlodipine)
- Beta-Blockers (e.g., Metoprolol)
- Probenecid
- Pregnancy

2. Skin Image Diagnosis



3. RUN SAFETY CHECK & DIAGNOSIS

4. Final Recommendation (Safety Check)

Diagnosis: Ba Cellulitis (Confidence: 99.52%)

Treatment: RECOMMENDED ALTERNATIVE: Clindamycin (oral) or appropriate cephalosporin based on local susceptibility

Safety Status: ✅ CONFLICT with Methotrexate! Standard Rx: Amoxicillin-Clavulanate (or local guideline-directed β-lactam or MRSA-covering agent when indicated)

1. Chronic Medications (Select all that apply)

- Insulin
- Oral Hypoglycemics (e.g., Metformin)
- Warfarin/Anticoagulants
- Methotrexate
- Amiodarone (QT-prolonging drug)
- Statins (e.g., Simvastatin, Atorvastatin)
- Calcium-Channel Blockers (e.g., Amlodipine)
- Beta-Blockers (e.g., Metoprolol)
- Probenecid
- Pregnancy

2. Skin Image Diagnosis



3. RUN SAFETY CHECK & DIAGNOSIS

4. Final Recommendation (Safety Check)

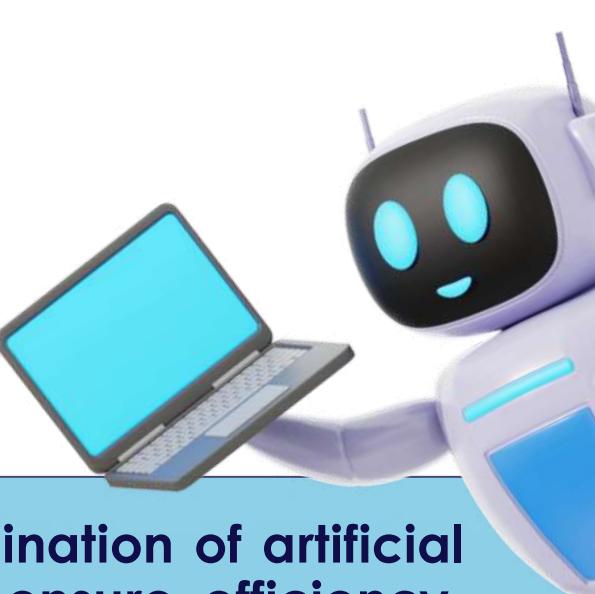
Diagnosis: Vi Shingles (Confidence: 94.71%)

Treatment: RECOMMENDED ALTERNATIVE: Acyclovir (if valacyclovir unavailable) or pain control and referral for severe cases

Safety Status: ✅ CONFLICT with Probenecid! Standard Rx: Valacyclovir or acyclovir (start within 72 hours when possible)



Tools & Technologies Used



The development of the proposed skin disease diagnosis and medical decision support system relied on a combination of artificial intelligence frameworks, data processing tools, and development environments. These tools were selected to ensure efficiency, accuracy, and scalability.

Programming Language :

Python was used as the primary programming language due to its extensive support for deep learning, data analysis, and scientific computing. Python enables rapid prototyping and seamless integration between machine learning models and system components.

Deep Learning Frameworks :

TensorFlow and Keras were utilized for building, training, and evaluating deep learning models. These frameworks provide high-level APIs that simplify the implementation of complex convolutional neural networks and support GPU acceleration for efficient training.

Model Architectures :

Several deep learning architectures were implemented and evaluated during the experimental phase:

- Custom Convolutional Neural Network (CNN)
- ResNet50 (Transfer Learning)
- ConvNeXt (Final Selected Model)

These architectures were chosen to compare traditional CNN approaches with modern state-of-the-art models.



Tools & Technologies Used



Data Processing & Analysis Tools :

NumPy and Pandas were used for data manipulation, preprocessing, and handling structured medical datasets. OpenCV and Pillow (PIL) were used for image loading and preprocessing operations. Scikit-learn was used for evaluation metrics and performance analysis

Development Environment :

Jupyter Notebook was used for experimentation, visualization, and step-by-step model development. This environment facilitated rapid testing and clear documentation of experiments and results.

Medical Knowledge Base :

A custom CSV-based medical knowledge dataset was manually created and used to store diseases, medications, contraindications, drug-drug interactions, and safe alternatives. This dataset serves as the foundation for the medication safety checking mechanism.

Visualization & Evaluation Tools :

Matplotlib and Seaborn were used to visualize training progress, accuracy, loss curves, and performance comparisons between models. These visualizations supported model selection and result interpretation.

Hardware & Execution Platform :

The models were trained and evaluated using GPU-enabled environments to accelerate deep learning operations. Cloud-based platforms such as Kaggle were used to manage datasets and execute computationally intensive experiments efficiently.



Tools & Technologies Used

Back-End :

Python Framework (Fast API) :
for building high-performance RESTful APIs



PostgreSQL :
for reliable and scalable relational data storage



PostgreSQL

SQLAlchemy :
as an ORM for efficient database interaction

SQLAlchemy

Token Based authentication for Secure system access





Tools & Technologies Used



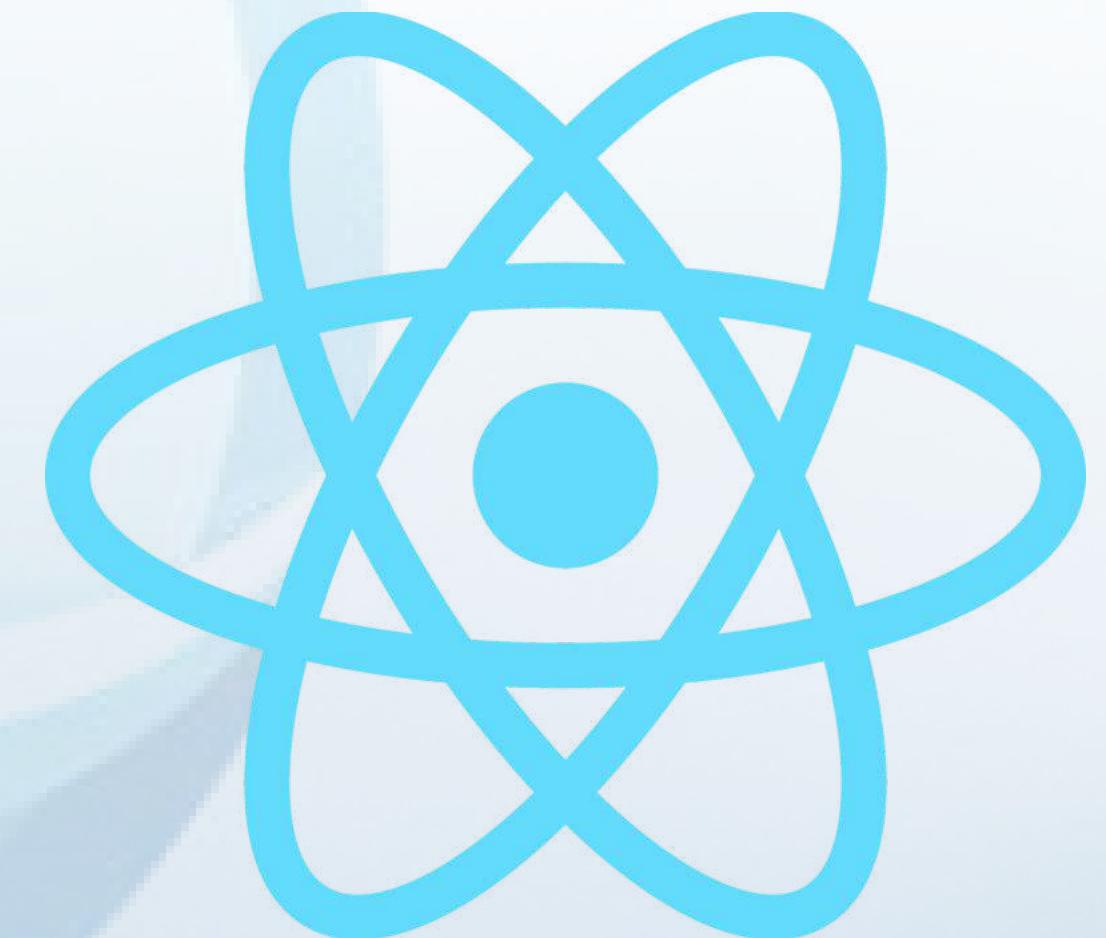
Front-End :

HTML5, CSS3, and JavaScript for structure and styling

Component-based architecture for better maintainability

React.js for building dynamic and responsive user interfaces

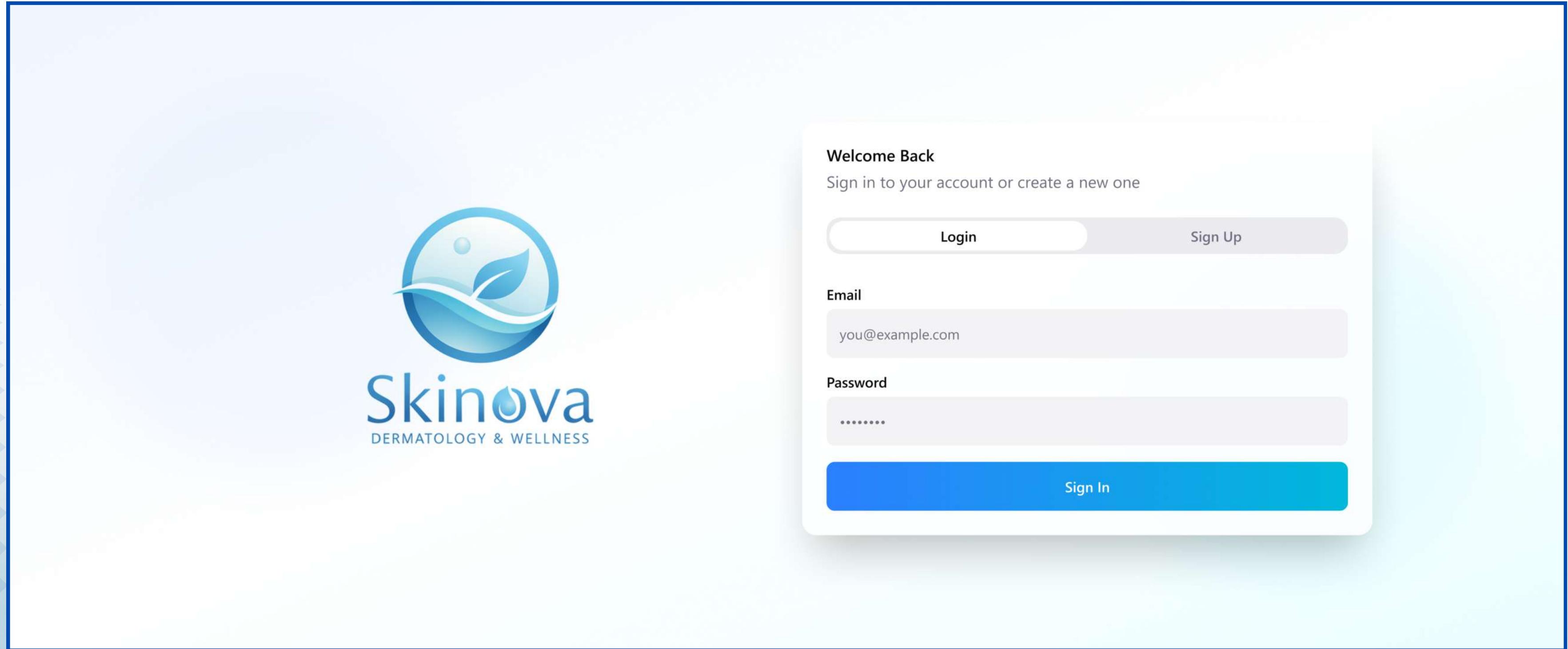
API integration with backend services





User-friendly Interfaces

Designed by
 Figma



The image shows a user-friendly login interface for Skinova Dermatology & Wellness. On the left, the Skinova logo is displayed. The main form is titled "Welcome Back" and prompts the user to "Sign in to your account or create a new one". It features two buttons: "Login" (highlighted in blue) and "Sign Up" (in grey). Below these are input fields for "Email" (containing "you@example.com") and "Password" (containing "....."). A large blue "Sign In" button is at the bottom of the form.

Welcome Back

Sign in to your account or create a new one

Login Sign Up

Email

you@example.com

Password

.....

Sign In



User-friendly Interfaces

Designed by
 Figma

Welcome Back

Sign in to your account or create a new one

[Login](#) [Sign Up](#)

Patient Name

Hoda Ashrf

Date of birth

mm/dd/yyyy

Email

you@example.com

Gender

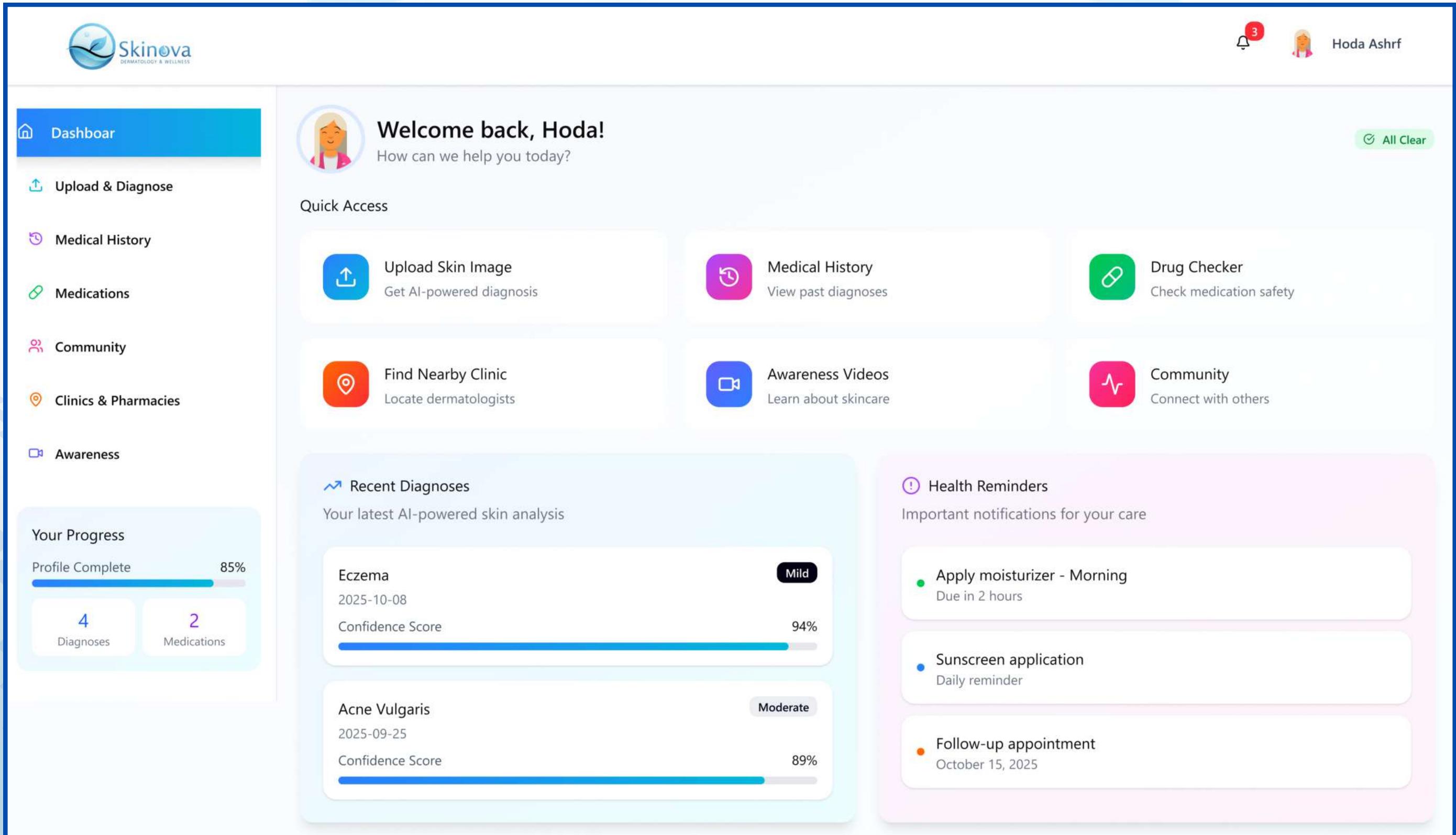
Male Female

Password

Confirm Password

[Create Account](#)

User-friendly Interfaces



The Skinova mobile application dashboard is designed to be user-friendly, providing quick access to various dermatology services and personalized health information.

Welcome back, Hoda!
How can we help you today?

Quick Access:

- Upload Skin Image: Get AI-powered diagnosis
- Medical History: View past diagnoses
- Drug Checker: Check medication safety
- Find Nearby Clinic: Locate dermatologists
- Awareness Videos: Learn about skincare
- Community: Connect with others

Your Progress:

Profile Complete: 85%

4 Diagnoses | 2 Medications

Recent Diagnoses:

Your latest AI-powered skin analysis

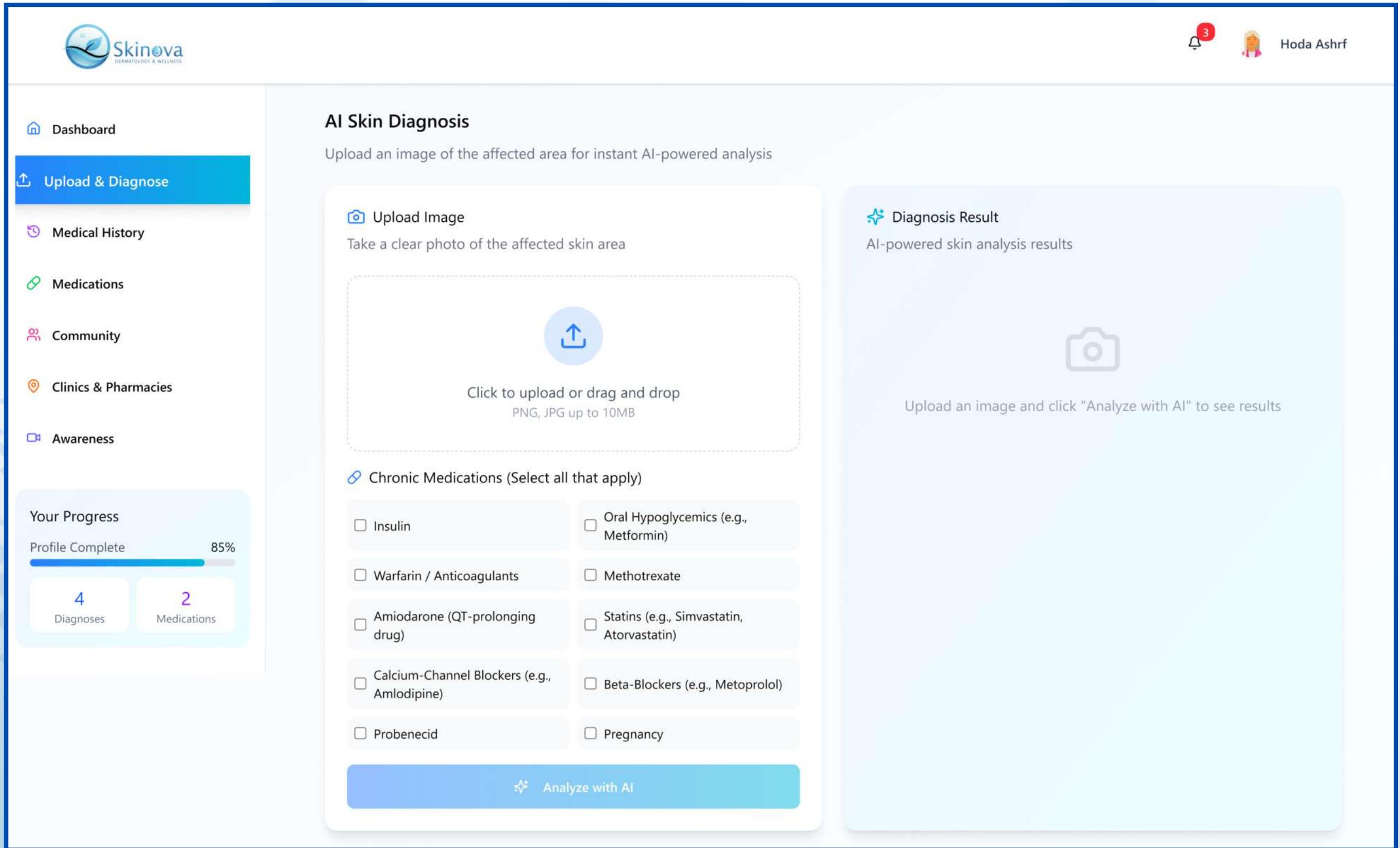
- Eczema (Mild) - 2025-10-08 | Confidence Score: 94%
- Acne Vulgaris (Moderate) - 2025-09-25 | Confidence Score: 89%

Health Reminders:

Important notifications for your care

- Apply moisturizer - Morning: Due in 2 hours
- Sunscreen application: Daily reminder
- Follow-up appointment: October 15, 2025

User-friendly Interfaces



The screenshot shows the Skinova mobile application interface. On the left is a vertical navigation bar with icons for Dashboard, Upload & Diagnose (highlighted in blue), Medical History, Medications, Community, Clinics & Pharmacies, and Awareness. Below this is a progress bar labeled "Your Progress" showing "Profile Complete" at 85%, with 4 Diagnoses and 2 Medications listed.

The main content area is titled "AI Skin Diagnosis" with the sub-instruction "Upload an image of the affected area for instant AI-powered analysis". It features a large central input field with a camera icon and the text "Click to upload or drag and drop PNG, JPG up to 10MB". To the right is a section titled "Diagnosis Result" with the sub-instruction "AI-powered skin analysis results" and a camera icon.

Below the input field is a list titled "Chronic Medications (Select all that apply)" with checkboxes for various medications:

- Insulin
- Oral Hypoglycemics (e.g., Metformin)
- Warfarin / Anticoagulants
- Methotrexate
- Amiodarone (QT-prolonging drug)
- Statins (e.g., Simvastatin, Atorvastatin)
- Calcium-Channel Blockers (e.g., Amlodipine)
- Beta-Blockers (e.g., Metoprolol)
- Probenecid
- Pregnancy

A blue button at the bottom right of the input field says "Analyze with AI".



User-friendly Interfaces

Designed by
 Figma

A screenshot of the Skinova Medical History dashboard. The left sidebar includes links for Dashboard, Upload & Diagnose, Medical History (which is selected and highlighted in blue), Medications, Community, Clinics & Pharmacies, and Awareness. A progress bar at the bottom indicates "Profile Complete" at 85%, with 4 Diagnoses and 2 Medications listed. The main area displays a "Diagnosis Timeline" with four entries: Atopic Dermatitis (Eczema) from 2025-10-08 (Severity: Moderate, Confidence: 92%, Medication: Hydrocortisone 1%, status: Ongoing), Acne Vulgaris from 2025-09-25 (Severity: Mild, Confidence: 89%, Medication: Benzoyl Peroxide 5%, status: Resolved), Contact Dermatitis from 2025-08-15 (Severity: Mild, Confidence: 87%, Medication: Calamine lotion, status: Resolved), and Psoriasis from 2025-07-10 (status: Ongoing). A "Record Details" section on the right shows a placeholder message: "Select a record to view details." A "Export Records" button is located in the top right corner.

Medical History
View and manage your past diagnoses and treatments

Diagnosis Timeline
Chronological view of your medical records

Atopic Dermatitis (Eczema)
2025-10-08 | Ongoing
Severity: Moderate | Confidence: 92%
Medication: Hydrocortisone 1%

Acne Vulgaris
2025-09-25 | Resolved
Severity: Mild | Confidence: 89%
Medication: Benzoyl Peroxide 5%

Contact Dermatitis
2025-08-15 | Resolved
Severity: Mild | Confidence: 87%
Medication: Calamine lotion

Psoriasis
2025-07-10 | Ongoing

Record Details
Select a record to view details.

Export Records

A screenshot of the Skinova Drug Interaction Checker dashboard. The left sidebar includes links for Dashboard, Upload & Diagnose, Medical History, Medications (selected and highlighted in blue), Community, Clinics & Pharmacies, and Awareness. A progress bar at the bottom indicates "Profile Complete" at 85%, with 4 Diagnoses and 2 Medications listed. The main area displays a "Current Medications" section with two entries: "Hydrocortisone 1%" (status: Current, taken 2x daily at 08:00 and 20:00) and "Cetirizine" (status: Chronic, taken 1x daily at 21:00). A "Drug Interactions" section shows a potential conflict between "Hydrocortisone + Ibuprofen" (Moderate risk, may increase risk of gastrointestinal side effects, safe alternative: Acetaminophen (Tylenol)). On the right, there are sections for "Medication Reminders" (with entries for 08:00, 20:00, and 21:00), "Medication Stats" (Active Medications: 2, Daily Reminders: 3, Conflicts Found: 1), and "Safety Tips".

Drug Interaction Checker
Manage your medications and check for potential interactions

Current Medications
Add and manage your medications

Hydrocortisone 1% Current
2x daily | 08:00 | 20:00

Cetirizine Chronic
1x daily | 21:00

Drug Interactions
Potential conflicts and safe alternatives

Hydrocortisone + Ibuprofen
Moderate
May increase risk of gastrointestinal side effects
Safe alternative: **Acetaminophen (Tylenol)**

Medication Reminders
Set up daily reminders

08:00 Hydrocortisone 1%
20:00 Hydrocortisone 1%
21:00 Cetirizine

Medication Stats

Active Medications: 2
Daily Reminders: 3
Conflicts Found: 1

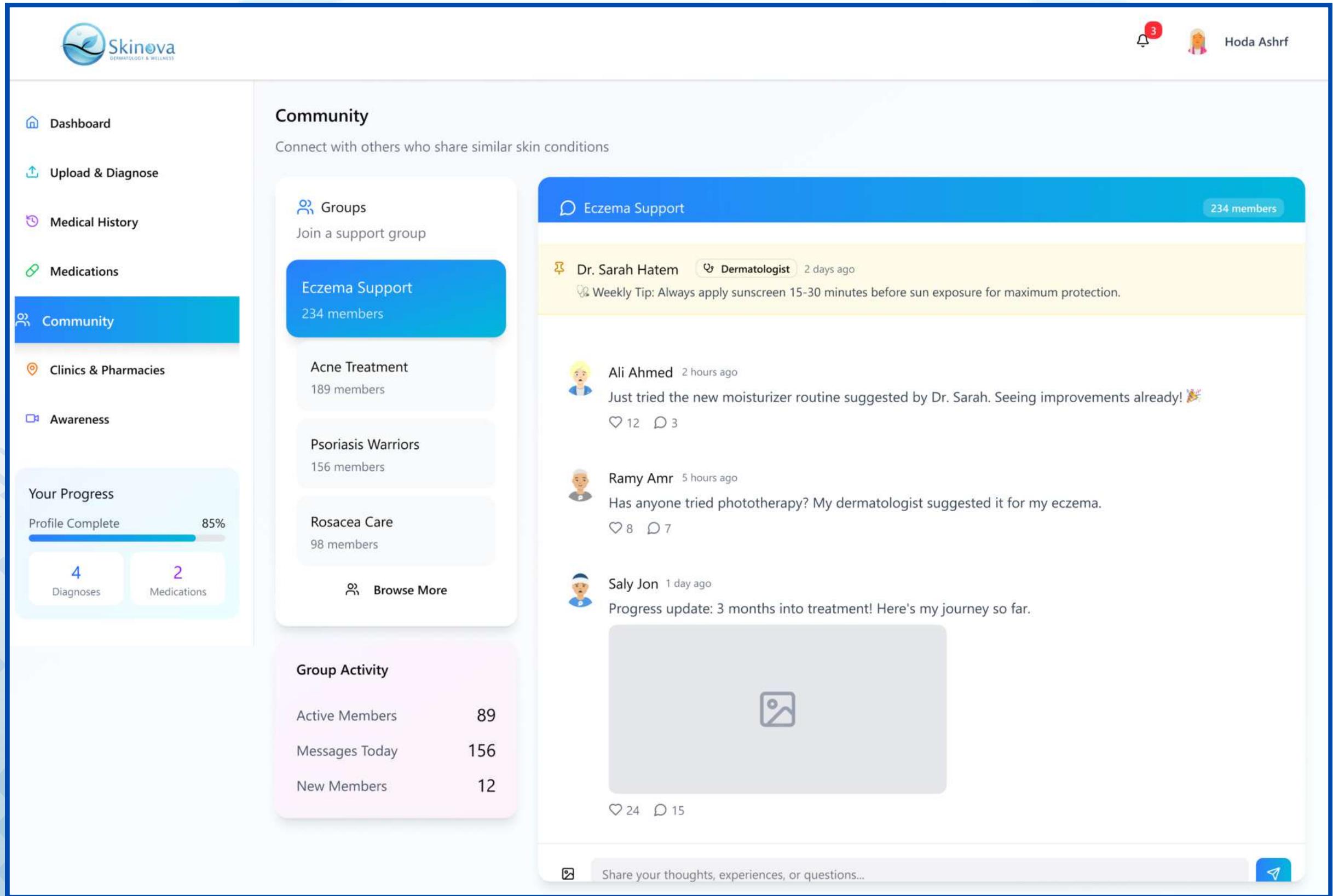
Safety Tips

- Always inform your doctor about all medications
- Keep medications in their original containers
- Never share prescription medications
- Check expiration dates regularly



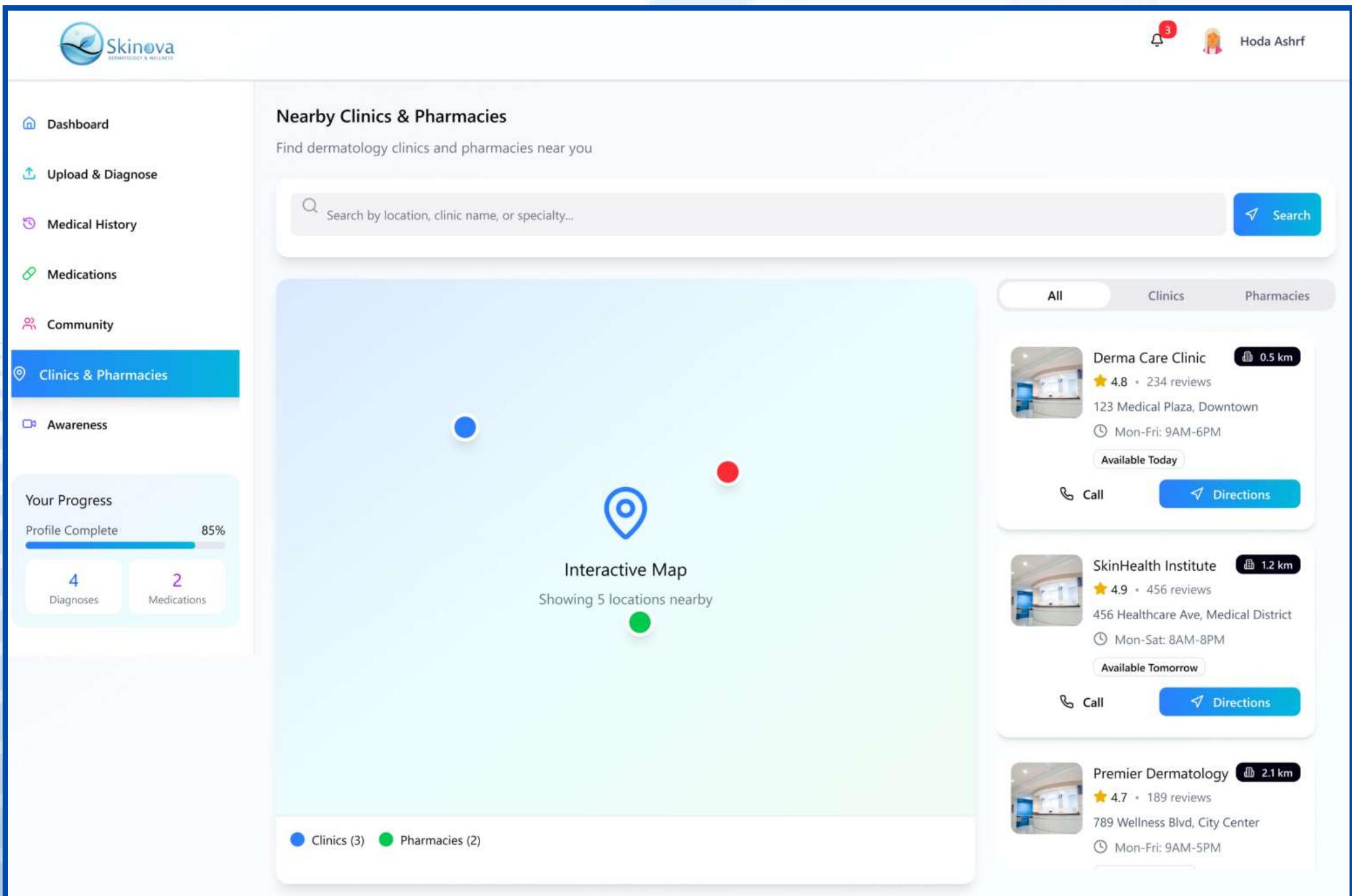
User-friendly Interfaces

Designed by
 Figma



The screenshot displays the Skinova mobile application's interface, specifically the 'Community' section. The top navigation bar includes the Skinova logo, a notification bell icon with a red '3' badge, and a user profile for 'Hoda Ashrf'. The left sidebar features a vertical navigation menu with icons and labels: Dashboard, Upload & Diagnose, Medical History, Medications, Community (which is highlighted in blue), Clinics & Pharmacies, and Awareness. Below this is a 'Your Progress' section showing a profile completion bar at 85%, 4 diagnoses, and 2 medications. The main content area is titled 'Community' with the sub-instruction 'Connect with others who share similar skin conditions'. It lists several support groups: 'Eczema Support' (234 members, currently selected), 'Acne Treatment' (189 members), 'Psoriasis Warriors' (156 members), and 'Rosacea Care' (98 members). A 'Browse More' button is available. At the bottom of this list is a 'Group Activity' section with statistics: Active Members (89), Messages Today (156), and New Members (12). The right side of the screen shows a detailed view of the 'Eczema Support' group. It features a blue header with the group name and member count. Posts from users Dr. Sarah Hatem (Dermatologist) and Ali Ahmed are visible, along with a post from Ramy Amr and a progress update from Saly Jon. A large, light-gray placeholder box with a camera icon is present, likely for sharing media. A footer bar at the bottom contains a text input field 'Share your thoughts, experiences, or questions...' and a blue send button.

User-friendly Interfaces



Nearby Clinics & Pharmacies

Find dermatology clinics and pharmacies near you

Search by location, clinic name, or specialty...

All Clinics Pharmacies

Derma Care Clinic 0.5 km
★ 4.8 • 234 reviews
123 Medical Plaza, Downtown
Mon-Fri: 9AM-6PM
Available Today

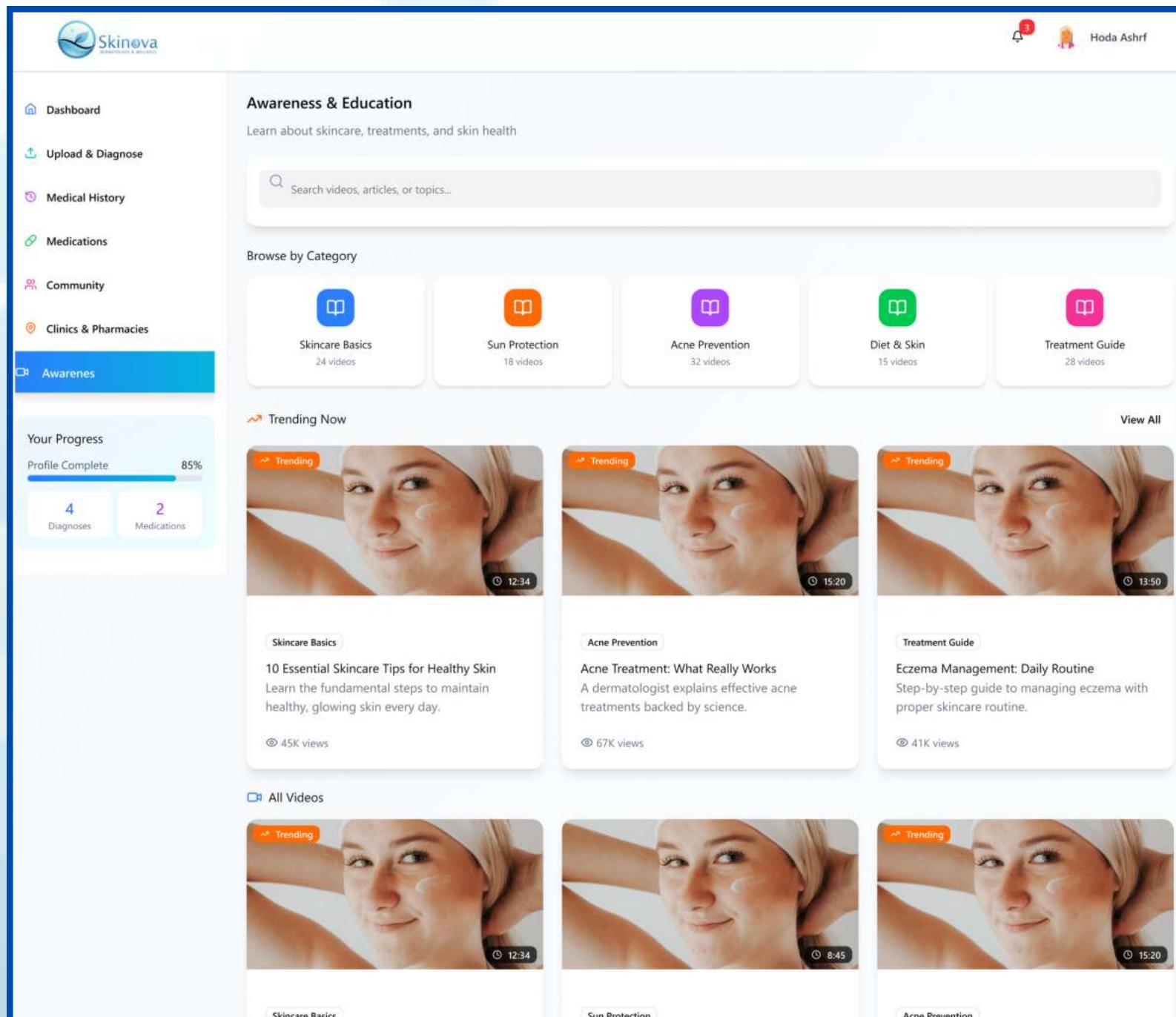
SkinHealth Institute 1.2 km
★ 4.9 • 456 reviews
456 Healthcare Ave, Medical District
Mon-Sat: 8AM-8PM
Available Tomorrow

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★ 4.7 • 189 reviews
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Mon-Fri: 9AM-5PM

Interactive Map
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Clinics (3) Pharmacies (2)

Your Progress
Profile Complete 85%
4 Diagnoses 2 Medications



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Awareness

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Profile Complete 85%

4 Diagnoses 2 Medications

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Learn the fundamental steps to maintain healthy, glowing skin every day.
45K views
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Acne Treatment: What Really Works
A dermatologist explains effective acne treatments backed by science.
67K views
- Treatment Guide**
Eczema Management: Daily Routine
Step-by-step guide to managing eczema with proper skincare routine.
41K views

All Videos

- Skincare Basics**
- Sun Protection**
- Acne Prevention**

Conclusion

This project presented an intelligent and integrated system for skin disease diagnosis that combines deep learning-based image classification with medical decision support.

By leveraging advanced convolutional neural network architectures, the system is capable of accurately identifying multiple skin diseases from uploaded images.

Unlike traditional AI-based diagnostic tools that focus solely on classification, the proposed system extends beyond diagnosis by incorporating a custom-built medical knowledge base.

This integration enables the system to verify treatment safety, detect drug-drug interactions, and recommend safe alternatives when necessary, thereby prioritizing patient safety.

Through a comparative experimental approach, multiple deep learning models were implemented and evaluated.

The ConvNeXt model was selected as the final diagnostic engine due to its superior performance, robustness, and balanced accuracy across a large number of skin disease classes.

In addition, the system emphasizes user-centered design by providing intuitive interfaces for image upload, medication selection, diagnosis visualization, and medical awareness.

Features such as medical history management, medication reminders, community support, and location-based services further enhance the practicality and real-world applicability of the system.

Overall, the proposed system demonstrates how artificial intelligence can be effectively combined with structured medical knowledge to support early diagnosis, improve treatment safety, and increase public awareness of skin diseases.

The results highlight the potential of such systems to assist both users and healthcare professionals while maintaining ethical and clinical responsibility.

Future Work

"While the current version of Skinova establishes a robust foundation for AI-driven dermatology, there is significant potential for further expansion. The following table outlines the strategic roadmap for future enhancements, focusing on improving diagnostic precision, system accessibility, and clinical trust."



| Category | Objective | Proposed Improvements |
|----------------------------|-------------------------|---|
| Model Optimization | Enhanced Performance | * Implementing Ensemble Learning by combining ConvNeXt with other architectures to increase classification stability. * Fine-tuning the model on a wider variety of skin tones to ensure fairness and inclusivity. |
| Medical Interpretability | Explainable AI (XAI) | * Integrating Grad-CAM or SHAP to provide visual explanations (heatmaps) for the AI's predictions, helping doctors trust the results. |
| Data Expansion | Broader Diagnosis | * Expanding the dataset to include rare skin diseases and pediatric-specific cases. * Incorporating Multi-modal data (combining images with patient symptoms and medical history) for higher diagnostic precision. |
| Feature Enrichment | Comprehensive Care | * Developing an AI-driven healing tracker that monitors changes in skin lesions over time through sequential photos. * Enhancing the Medication Safety Check with a larger, real-time database of drug interactions. |
| Deployment & Accessibility | Platform Expansion | * Transitioning from a web-based app to a Native Mobile Application (iOS/Android). * Utilizing TensorFlow Lite for "Edge AI" to enable offline diagnosis in remote areas. |
| Clinical Integration | Telehealth Capabilities | * Building a secure Doctor-Patient Portal for real-time consultations and digital prescription management. |



Project Timeline Plan :

"Before August 2025, the team was assembled, essential courses were studied, and a feasibility study was conducted to evaluate the project's potential."

| Date Range | Phase / Task | Duration | Description |
|-----------------------|---|----------|--|
| Aug 1 – Aug 15, 2025 | Introduction | 2 weeks | Drafting the introduction, defining the problem, collecting basic statistics on skin diseases. |
| Aug 16 – Sep 15, 2025 | Literature Review | 1 month | Reviewing previous studies (CNN, ResNet, EfficientNet,), writing comparisons between research papers. |
| Sep 16 – Sep 30, 2025 | Problem Statement | 2 weeks | Formulating the problem clearly and linking it to gaps in current systems. |
| Oct 1 – Oct 15, 2025 | Key Features | 2 weeks | Defining features (image upload, medication reminders, community, maps,). |
| Oct 16 – Oct 31, 2025 | System Requirements | 2 weeks | Writing functional and non-functional requirements + hardware/software needs. |
| Nov 1 – Nov 15, 2025 | Methodology (Design + Datasets) | 2 weeks | Defining methodology, selecting datasets (HAM10000, ResNet, ConvNeXt). |
| Nov 16 – Dec 15, 2025 | Implementation (Model Training + Preprocessing) | 1 month | Training models, data preprocessing, augmentation, handling imbalance. |
| Dec 16 – Dec 31, 2025 | Tools & Technologies | 2 weeks | Documenting tools (Python, TensorFlow, Keras, UI Framework). |
| Jan 1 – Jan 10, 2026 | User-friendly Interfaces | 10 days | Designing user interfaces (upload images, results, community, maps). |
| Jan 11 – Jan 20, 2026 | Testing & Evaluation | 10 days | Testing performance, model accuracy, response speed, data security. |
| Jan 21 – Jan 25, 2026 | Conclusion | 5 days | Writing final results and linking them to objectives. |
| Jan 26 – Jan 30, 2026 | Future Work | 5 days | Suggesting future improvements (expanding datasets, enhancing medical interpretability). |
| Jan 31 – Feb 1, 2026 | References + Final Review | 2 days | Final review + formatting references. |

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Any questions?

THANK
YOU!

