Skin Health Companion Application

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Overview

Introduction

- Skin diseases are among the most common health issues worldwide that affect **millions of people** with varying severity. **Early diagnosis** is crucial for effective treatment, but access to dermatological care remains limited, especially in remote regions.

- **Skin Health Companion** is designed to bridge this gap by leveraging AI for automated skin disease classification, providing users with fast, accessible preliminary screening and essential dermatological guidance.

Goals of the Project

- **Application Track:** Develop a mobile-friendly AI diagnosis tool.
- Ensure a user-friendly design with accessibility in mind.
- Prioritize privacy and security: user data remains protected and easily shareable with healthcare providers.

Background & Literature Review

- **AI-driven image analysis** has begun to revolutionize medical diagnostics of all fields including dermatology.
- The classification of skin diseases is considerably more challenging due to the *visual similarities* between conditions.
- We look at the following two deep learning-based approaches to build a state-of-the-art model for the classification of skin conditions:
  - **CNN** - *Comparative Study of Multiple CNN Models for Classification of 23 Skin Diseases - Amina Aboulmira et al.*
  - **Transformer** - *Enhancing Skin Disease Classification Leveraging Transformer-based Deep Learning Architectures and Explainable AI - Jayanth Mohan et al.*

Finetuned CNN

- **CNNs** - widely used for medical image classification due to hierarchical feature extraction.
- The study evaluates various CNN-based models for end-to-end retraining for 23 skin diseases.
- **Best performing models:** *DenseNet201, DenseNet161, ResNet50, EfficientNet-B0, and MobileNetV2*

Finetuned Transformer

- **Transformers** - leverage self-attention mechanisms, providing strong feature representations.
- Captures global dependencies rather than localized features.
- **Best performing models:** *DinoV2 (facebook/dinov2-base), SwinT (microsoft/swin-tiny-patch4-window7-224), and ViT (google/vit-base-patch16-224)*

Datasets & Preprocessing

- **Datasets used:**
  - DermNet
  - HAM10000
- **Class Imbalance:**
  - *Samples/Class* varies across conditions.
  - Handled using **Weighted Random Sampler**.
- **Data Augmentation Techniques:**
  - **Random Horizontal Flip** - Helps generalization across orientations.
  - **Rotation** - Enhances the robustness of the model to different angles.
  - **ColorJitter** - Adjusts brightness, contrast, saturation, and hue variations.
  - **Normalization** - Standardizes pixel values with ImageNet weights.
  - **Resizing** - Ensures uniform $(224, 224)$ input dimensions.

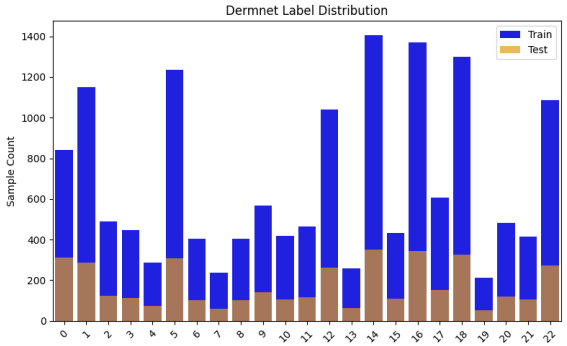
DermNet Dataset

- Dermatology-focused dataset containing skin disease images.
- Contains multiple classes of skin conditions that include acne, eczema, melanoma, and others.
- **Challenges:**
  - Presence of watermarks in images.
  - Most of the images are of Caucasian skin tones, limiting diversity.
  - Not all classes in the Dataset are Mutually Exclusive.
  - Noise such as microscopic images.

DermNet Dataset

0	Acne and Rosacea Photos	840	312
1	Actinic Keratosis Basal Cell Carcinoma and other Malignant Lesions	1149	288
2	Atopic Dermatitis Photos	489	123
3	Bullous Disease Photos	448	113
4	Cellulitis Impetigo and other Bacterial Infections	288	73
5	Eczema Photos	1235	309
6	Exanthems and Drug Eruptions	404	101
7	Hair Loss Photos Alopecia and other Hair Diseases	239	60
8	Herpes HPV and other STDs Photos	405	102
9	Light Diseases and Disorders of Pigmentation	568	143
10	Lupus and other Connective Tissue diseases	420	105
11	Melanoma Skin Cancer Nevi and Moles	463	116
12	Nail Fungus and other Nail Disease	1040	261
13	Poison Ivy Photos and other Contact Dermatitis	260	65
14	Psoriasis pictures Lichen Planus and related diseases	1405	352
15	Scabies Lyme Disease and other Infestations and Bites	431	108
16	Seborrheic Keratoses and other Benign Tumors	1371	343
17	Systemic Disease	606	152
18	Tinea Ringworm Candidiasis and other Fungal Infections	1300	325
19	Urticaria Hives	212	53
20	Vascular Tumors	482	121
21	Vasculitis Photos	416	105
22	Warts Molluscum and other Viral Infections	1086	272

DermNet Dataset



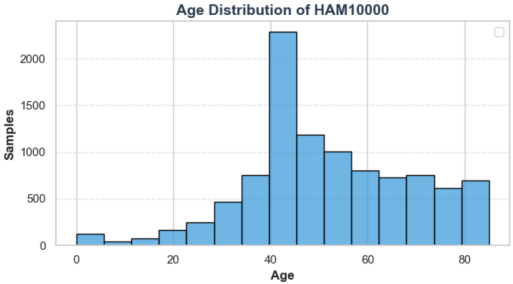
HAM10000 Dataset

- Large dataset used for melanoma classification.
- **Labels:** Includes multiple categories for skin lesions. Contains melanoma, benign lesions, and other abnormalities.

HAM10000 Dataset

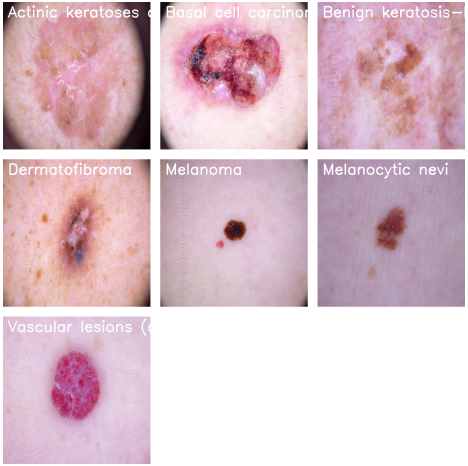
	lesion_id	image_id	dx	dx_type	age	sex	localization	dataset
0	HAM_0000118	ISIC_0027419	bkl	histo	80	male	scalp	vidir_modern
1	HAM_0000118	ISIC_0025030	bkl	histo	80	male	scalp	vidir_modern
2	HAM_0002730	ISIC_0026769	bkl	histo	80	male	scalp	vidir_modern
3	HAM_0002730	ISIC_0025661	bkl	histo	80	male	scalp	vidir_modern
4	HAM_0001466	ISIC_0031633	bkl	histo	75	male	ear	vidir_modern
5	HAM_0001466	ISIC_0027850	bkl	histo	75	male	ear	vidir_modern
6	HAM_0002761	ISIC_0029176	bkl	histo	60	male	face	vidir_modern

```
Total Images:  10000
Unique Classes [dx]:  ['bkl', 'nv', 'df', 'mel', 'vasc', 'bcc', 'akiec']
Unique Datasets: ['vidir_modern', 'rosendahl', 'vienna_dias', 'vidir_molemax']
Maintining same 80:20 train-test split
```



HAM10000 Dataset

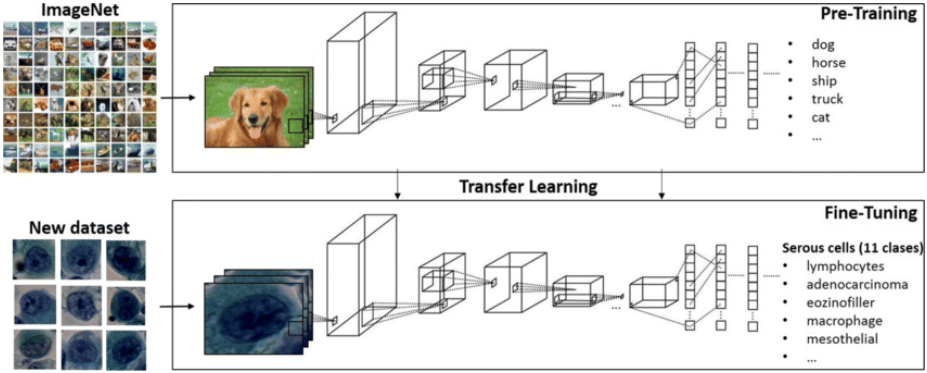
	Labels	NumSamples
0	Actinic keratoses and intraepithelial carcinoma / Bowen's disease	327
1	Basal cell carcinoma	514
2	Benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratoses)	1099
3	Dermatofibroma	115
4	Melanoma	1113
5	Melanocytic nevi	6705
6	Vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage)	142



CNN

- Trained on the **DermNet** dataset.
- **Retraining Strategies:**
  - **End-to-end training** vs. **Freezing layers**.
  - Freezing layers led to poor performance (**Top-1 Accuracy** $< 20\%$).
  - Adopted **end-to-end retraining** for better results.
- **Models Evaluated:**
  - MobileNetV2, EfficientNet-B0, ResNet50, DenseNet201, DenseNet161.

CNN



Computational Constraints:

- **Google Colab:** Free Tier limitations.
- **Laptop GPU**

Transformer

- **Dataset Used:** Combination of **DermNet** and **HAM10000** (23+7=30 Classes).
- **Strategy: End-to-End Re-Training**
  - Achieves **78.5% Top-1 accuracy** for DinoV2.
- **Models Tested:**
  - DinoV2, SwinT, ViT.
- **Alternative Strategy: Freezing Layers with a final unfrozen MLP Classifier**
  - Performance similar to finetuned CNN models but slightly worse.

Metrics

- **Chosen Training Metric: Accuracy**
  - **Standard benchmark for multi-class classification** - Accuracy is widely used in deep learning research, making results comparable to prior studies.
  - **Interpretability for real-world application** - Accuracy provides a direct and intuitive measure of correctness, making it easy for users to understand model performance.
- **Evaluation Metrics Used for Model Assessment**
  - **Precision** - Measures the percentage of correctly predicted positive cases.
  - **Recall** - Ability to detect true positive cases.
  - **F1-score** - Balances precision and recall, providing a more stable metric.
- **Confusion Matrix Analysis**

Metrics

Model	Training Speed	Complexity	Layers	# Parameters
MobileNetV2	Fast	Low	53	3.5M
EfficientNet-B0	Medium	Low-Medium	82	5.3M
ResNet50	Medium	High	50	25.6M
DenseNet201	Slow	High	201	20M
DenseNet161	Slow	High	161	26M

Table: Comparison of CNN Architectures

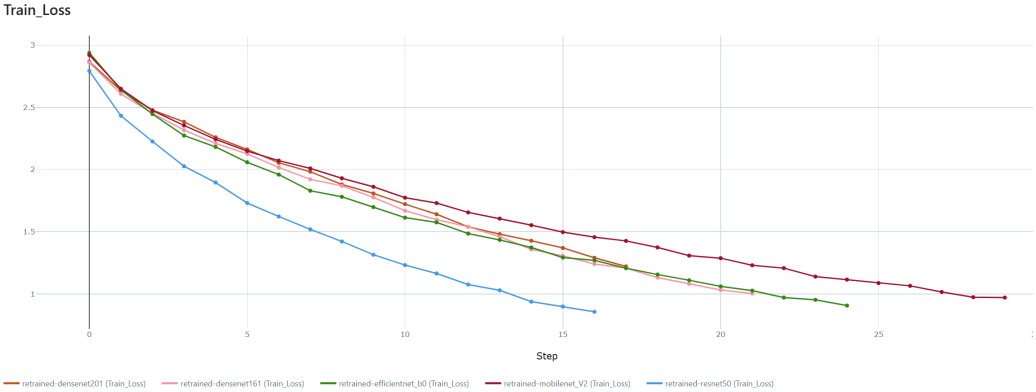
Model	Training Speed	Complexity	Layers	# Parameters
DinoV2	Medium	High	12	86M
SwinT	Fast	Medium	4	28M
ViT	Slow	High	12	85M

Table: Comparison of Transformer Architectures

CNN Training

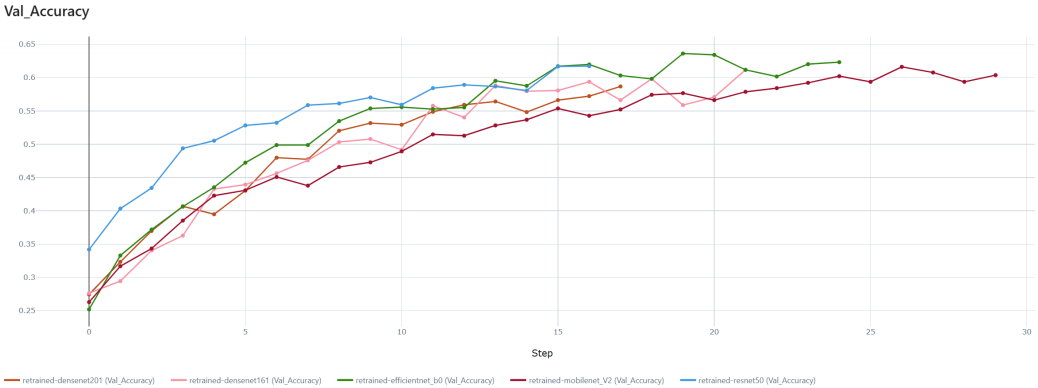
- **Training Setup**
  - Batch size: **16**, maximum epochs: **50** (with early stopping if validation loss doesn't decrease every 5 epochs).
- **Performance Comparison Across CNN Models**
  - All CNNs performed similarly:
    - **Top-1 Accuracy**: **56-63%**
    - **Top-5 Accuracy**: **80-85%**
- **Class-wise Performance Insights**
  - Certain classes perform better due to distinct pigmentation or body location.
  - Other classes suffer misclassification due to visual overlap and ambiguous symptoms or mislabeled ground truths.
- **Final Model Choice: EfficientNet-B0**
  - Chosen for lightweight architecture, suitable for offline inference.

CNN Training

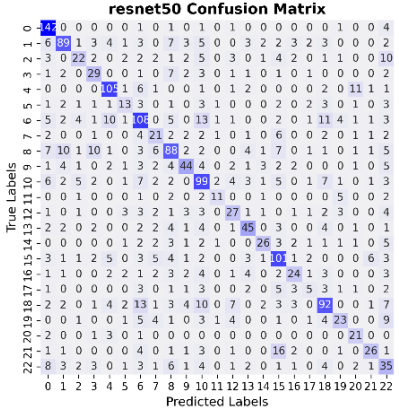


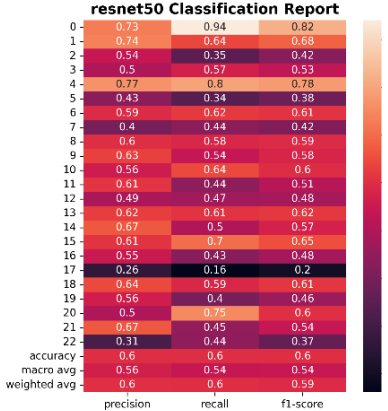
CNN Training

CNN Training



CNN Training

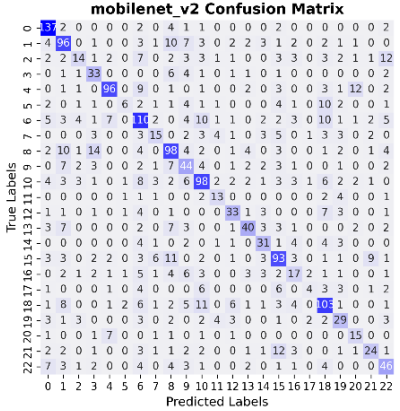


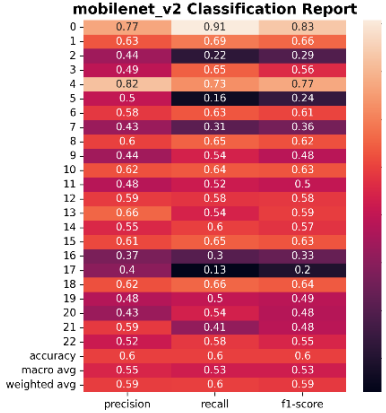


Top-1 Accuracy: 59.74%

Top-5 Accuracy: 83.92%

CNN Training

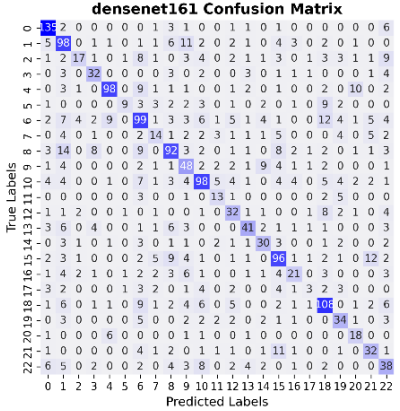


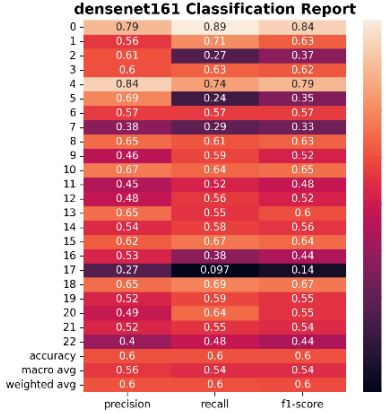


Top-1 Accuracy: 59.69%

Top-5 Accuracy: 83.97%

CNN Training

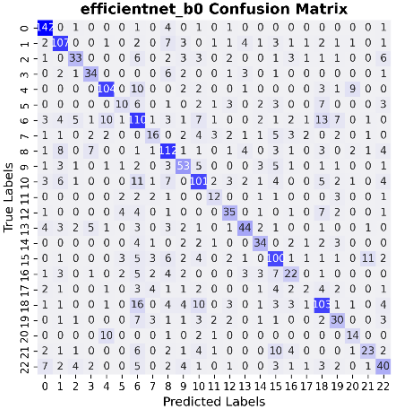


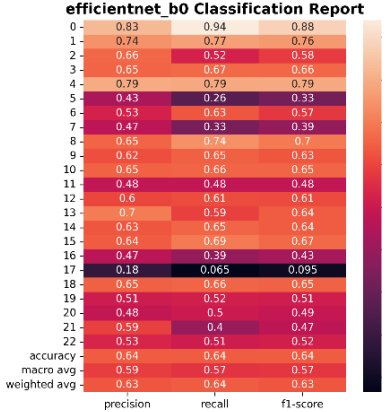


Top-1 Accuracy: 60.24%

Top-5 Accuracy: 84.22%

CNN Training

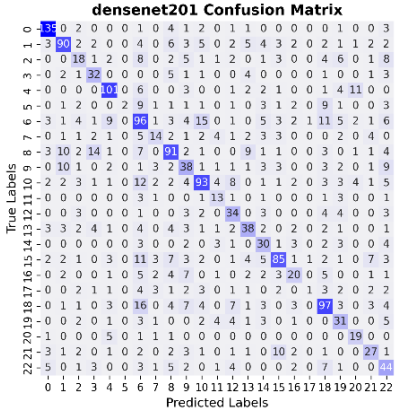


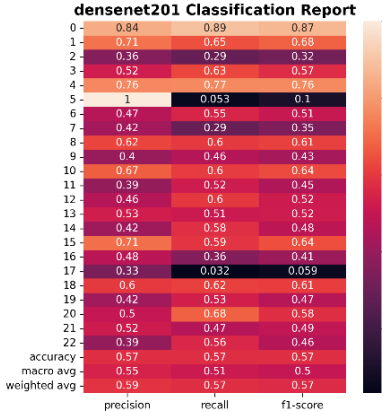


Top-1 Accuracy: 63.99%

Top-5 Accuracy: 86.26%

CNN Training





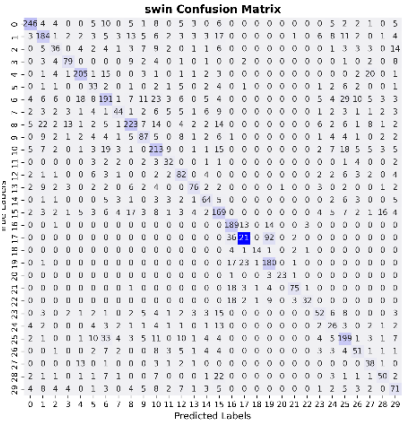
Top-1 Accuracy: 57.39%

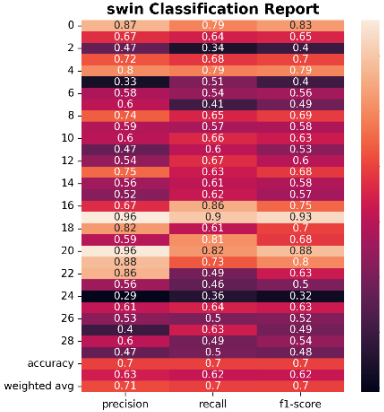
Top-5 Accuracy: 82.97%

Transformer Training

- **Training Setup**
  - Batch size: **32**, learning rate: **5e-5**, epochs: **10**.
- **Accuracy Comparison with Reference Paper**
  - Achieved Top-1 Accuracy: 78%, matching reference paper for DinoV2.
- **Final Model Choice: DinoV2**
  - Best performing Transformer Model for skin disease classification.

Transformer Training

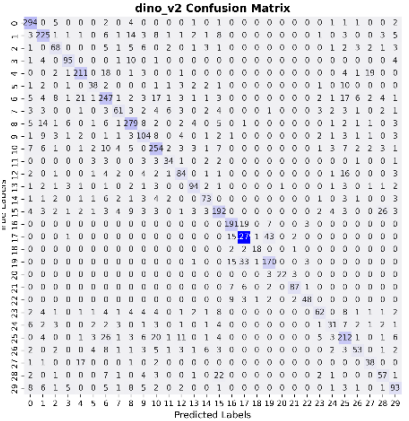


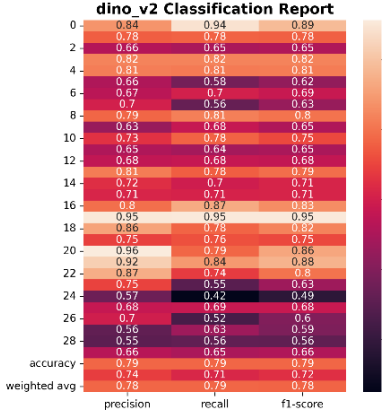


Top-1 Accuracy: 69.53%

Top-3 Accuracy: 87.83%

Transformer Training

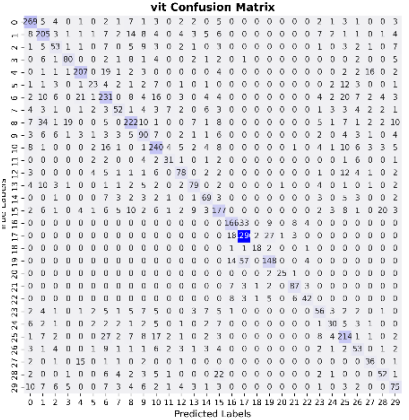


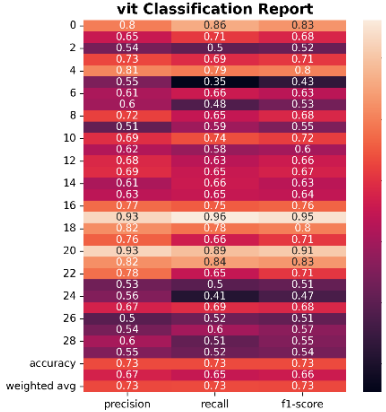


Top-1 Accuracy: 78.50%

Top-3 Accuracy: 92.41%

Transformer Training

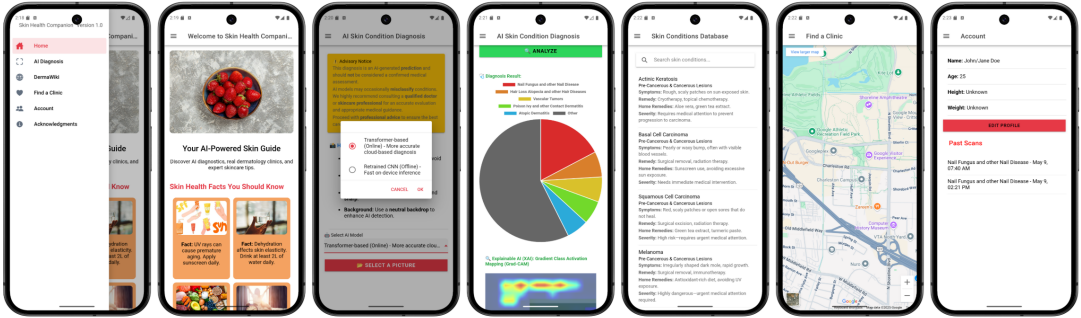




Top-1 Accuracy: 73.24%

Top-3 Accuracy: 90.22%

App Tour


Skin Health Companion Version 1.0
Home
AI Diagnosis
DermaWiki
Find a Clinic
Account
Acknowledgments
Welcome to Skin Health Compani...
Your AI-Powered Skin Guide
Discover AI diagnostics, real dermatology clinics, and expert skincare tips.
Skin Health Facts You Should Know
Fact: UV rays can cause premature aging. Apply sunscreen daily.
Fact: Dehydration affects skin elasticity. Drink at least 2L of water daily.
AI Skin Condition Diagnosis
Advisory Notice
Transformer-based (Online) - More accurate cloud-based diagnosis
Retrained CNN (Offline) - Fast on-device inference
CANCEL
OK
Background: Use a neutral backdrop to enhance AI detection.
Select AI Model
Transformer-based (Online) - More accurate clou...
SELECT A PICTURE
AI Skin Condition Diagnosis
ANALYZE
Diagnosis Result:
Nail Fungus and other Nail Disease
Nail Loss (Onycholysis) and other Nail Diseases
Vascular Tumors
Poison Ivy and other Contact Dermatitis
Atopic Dermatitis
Other
Explainable AI (XAI): Gradient Class Activation Mapping (Grad-CAM)
Skin Conditions Database
Search skin conditions...
Actinic Keratosis
Pre-Cancerous & Cancerous Lesions
Symptoms: Rough, scaly patches on sun-exposed skin.
Remedy: Cryotherapy, topical chemotherapy.
Home Remedies: Aloe vera, green tea extract.
Severity: Requires medical attention to prevent progression to carcinoma.
Basal Cell Carcinoma
Pre-Cancerous & Cancerous Lesions
Symptoms: Pearly or waxy bump, often with visible blood vessels.
Remedy: Surgical removal, radiation therapy.
Home Remedies: Sunscreen use, avoiding excessive sun exposure.
Severity: Needs immediate medical intervention.
Squamous Cell Carcinoma
Pre-Cancerous & Cancerous Lesions
Symptoms: Red, scaly patches or open sores that do not heal.
Remedy: Surgical excision, radiation therapy.
Home Remedies: Green tea extract, turmeric paste.
Severity: High risk—requires urgent medical attention.
Melanoma
Pre-Cancerous & Cancerous Lesions
Symptoms: Irregularly shaped dark mole, rapid growth.
Remedy: Surgical removal, immunotherapy.
Home Remedies: Antioxidant-rich diet, avoiding UV exposure.
Severity: Highly dangerous—urgent medical attention required.
Find a Clinic
Account
Name: John/Jane Doe
Age: 25
Height: Unknown
Weight: Unknown
EDIT PROFILE
Past Scans
Nail Fungus and other Nail Disease - May 9, 07:40 AM
Nail Fungus and other Nail Disease - May 9, 02:21 PM

App Walkthrough

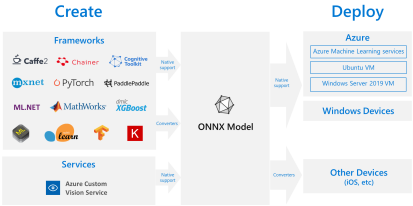
- **Homepage**: General Skincare Guidance
  - Provides skincare tips and advice for common conditions.
- **AI Diagnosis**: Core of the app - Skin Condition Classification
  - **Model selection**: CNN vs Transformer.
  - Image upload and preprocessing.
  - Real-time classification results for user feedback.
- **Find a Clinic**: Locating Dermatologists Nearby using Google Maps
- **DermaWiki**: Repository compiled using GPT of skin conditions, symptoms, and remedies.
- **Account & Scan History**: Secure Local Storage
  - On-device storage (not cloud-based) for privacy protection.
  - Direct doctor-ready reports for medical consultation.

Online vs Offline Inference

- **Importance of Offline Model Availability**
  - Essential for **rural areas** with minimal internet access.
  - Ensures AI-powered diagnosis in remote conditions.
- **EfficientNet - Based On-Device Inference**
  - Optimized for **fast processing on mobile devices**.
  - Enables real-time classification without connectivity dependence.
- **Cloud-Based AI for Advanced Online Diagnosis**
  - Transformer-based inference via cloud API for high-accuracy classification.
  - Suitable for users with stable internet connectivity.

On-Device: Intermediate Representations & ONNX

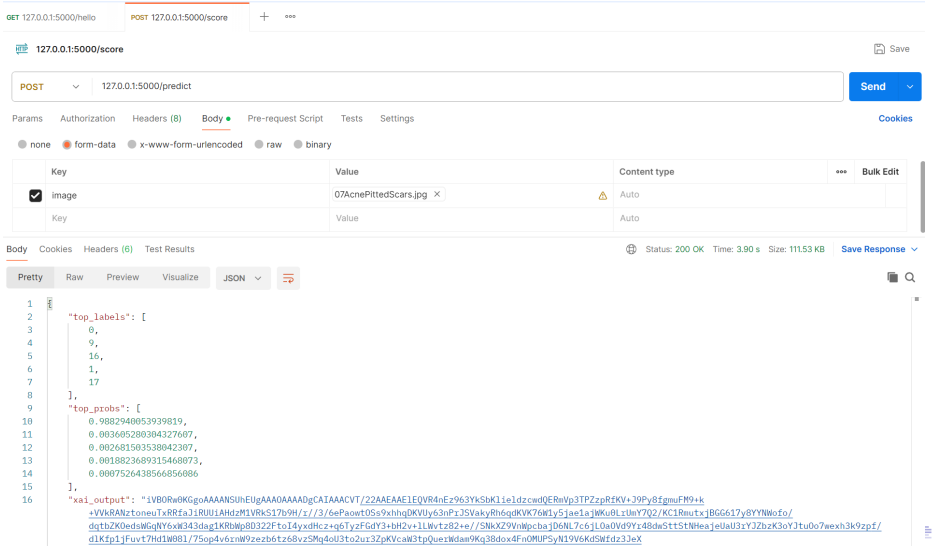
- **Understanding Intermediate Representations**
  - Internal feature extraction layers before final classification.
  - Helps optimize AI models for mobile efficiency.
- **ONNX for Mobile Deployment**
  - Converts AI models to ONNX format for optimized execution.
  - Ensures fast inference on low-power devices.



Cloud Deployment & REST API Workflow

- **Deployment Architecture for Transformer Models**
  - Using **cloud-hosted AI models** for inference.
  - Enables powerful computation while keeping mobile models lightweight.
- **REST API Workflow**
  - **Payload Structure**
  - **Result Processing**

REST API


GET 127.0.0.1:5000/hello
POST 127.0.0.1:5000/score
127.0.0.1:5000/score
Save
POST
127.0.0.1:5000/predict
Send
Params
Authorization
Headers (8)
Body
Pre-request Script
Tests
Settings
Cookies
none
form-data
x-www-form-urlencoded
raw
binary
Key
Value
Content type
Bulk Edit
image
07AcnePittedScars.jpg
Auto
Key
Value
Auto
Body
Cookies
Headers (6)
Test Results
Status: 200 OK
Time: 3.90 s
Size: 111.53 KB
Save Response
Pretty
Raw
Preview
Visualize
JSON
{
"top_labels": [
0,
9,
16,
1,
17
],
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Limitations & Future Work

- Increasing dataset diversity for model generalization across skin tones.
- **Integrating Model Explainability**
  - Using **SHAP** for feature importance analysis.
- Including images of normal skin to improve model differentiation between healthy vs diseased skin.
- Watermark Removal
- Exploring Lightweight Vision Transformer Models for Mobile

References

- **Research Papers**
  1. CNN-based Skin Disease Classification. ResearchGate.
  2. Vision Transformer Approach for Skin Condition Analysis. ScienceDirect.
- **Frameworks and Libraries**
  - PyTorch: `https://pytorch.org/`
  - HuggingFace Transformers: `https://huggingface.co/docs/transformers/index`
  - ONNX Runtime: `https://onnxruntime.ai/`
- **Development Tools**
  - Ionic Framework: `https://ionicframework.com/docs`
  - Google Cloud Functions: `https://cloud.google.com/functions/docs`
- **Model Links**
  - DinoV2: `https://huggingface.co/facebook/dinov2-base`
  - SwinT: `https://huggingface.co/microsoft/swin-tiny-patch4-window7-224`
  - ViT: `https://huggingface.co/google/vit-base-patch16-224`

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