

SKIN DISEASE CLASSIFICATION USING CNNS

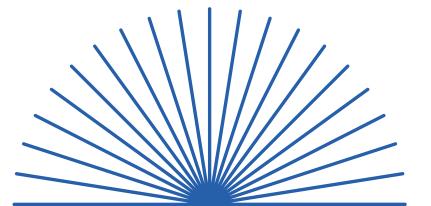
Project Presentation

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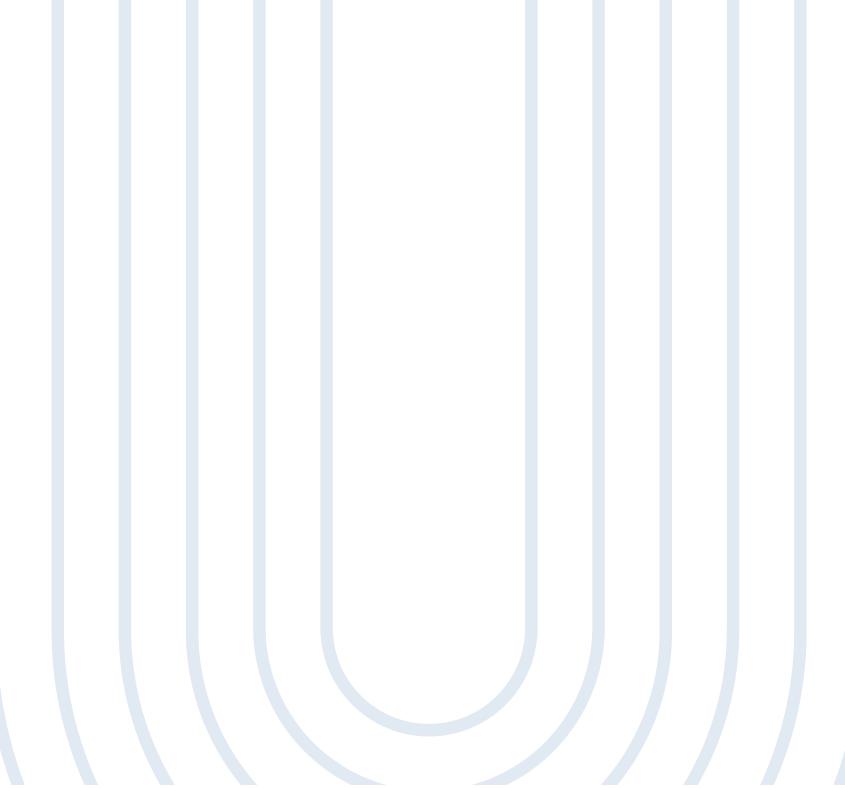
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Project Overview

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- Goal: Classify different types of skin diseases from medical images
- Dataset: DermNet skin disease dataset (Kaggle)
- Contains around 20+ disease classes (Acne, Eczema, Psoriasis, etc.)
- Each class has several hundred images (train/test folders)
- Task type: Multi-class Image Classification
- Approach: Baseline CNN + Pretrained Model (Transfer Learning)



Dermnet

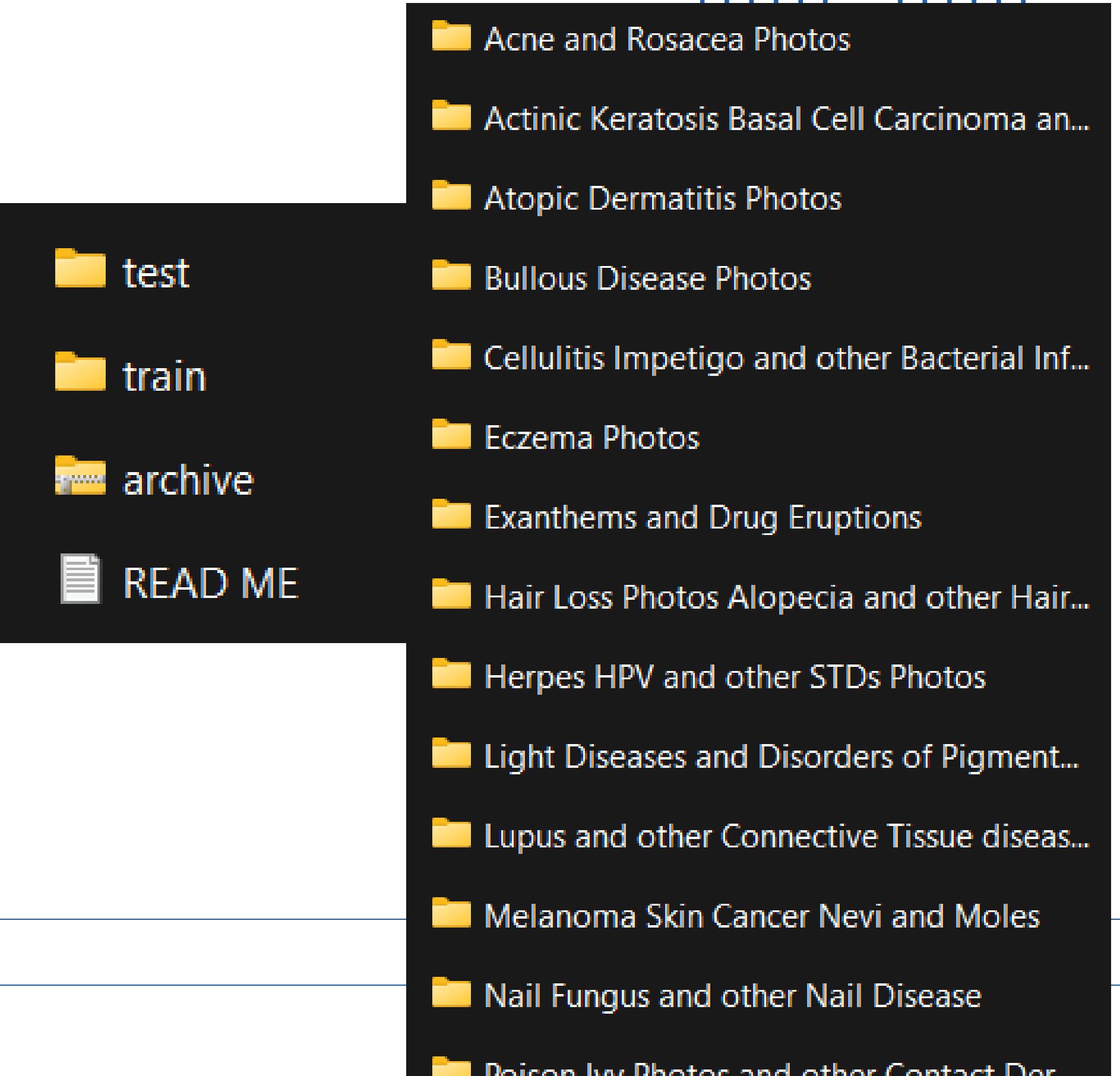
Image data for 23 categories of skin diseases



DATASET STRUCTURE

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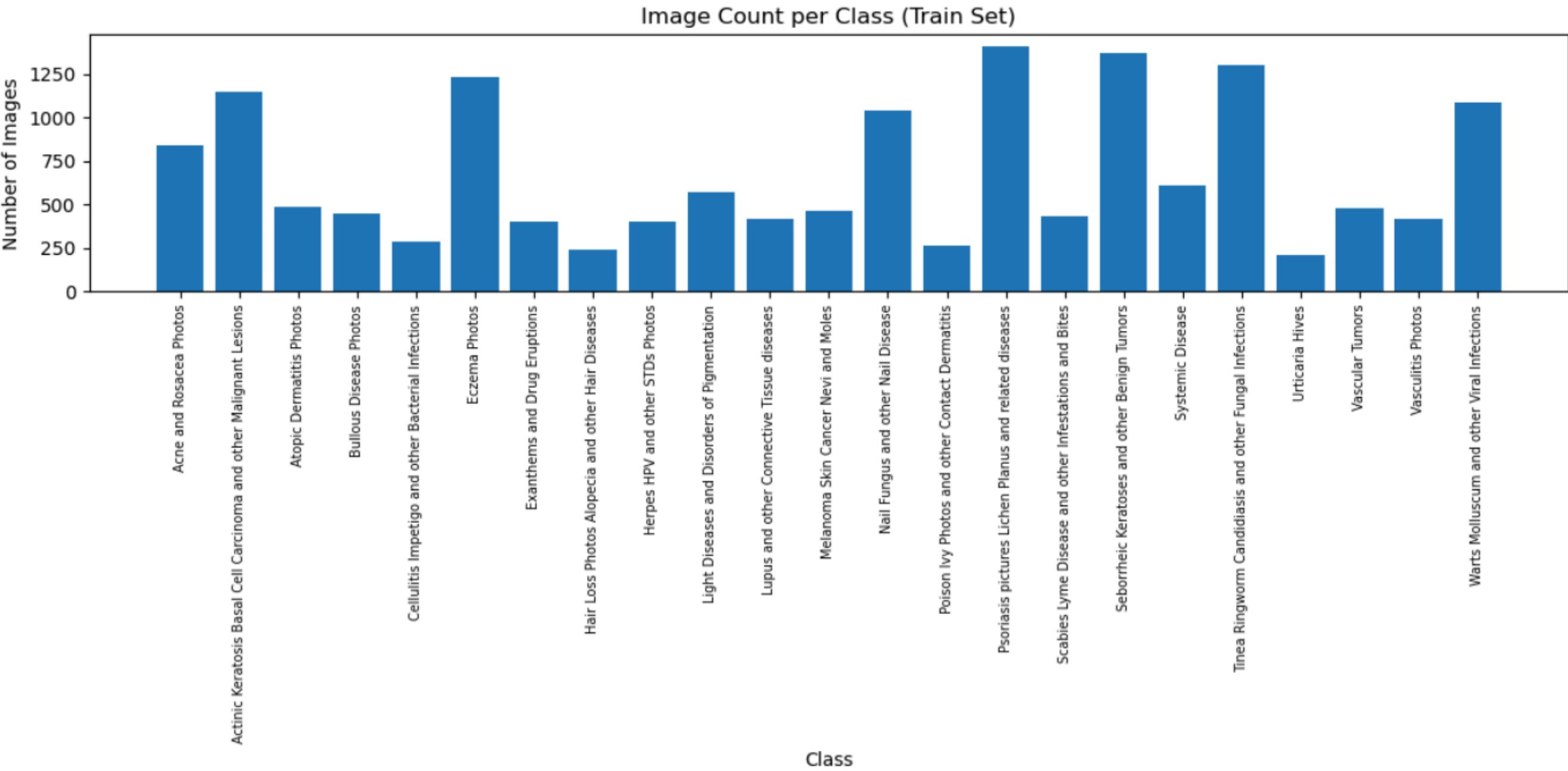
- Dataset divided into train and test folders
- Each folder contains subfolders, one per disease class
- Example classes:
 - Acne and Rosacea Photos
 - Eczema Photos
 - Psoriasis and related diseases
 - Nail Fungus and other Nail Disease
 - Herpes, HPV, and other STDs
- Each subfolder contains several hundred images (.jpg, .jpeg)



DATA INSIGHTS

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- Total of 23 classes of skin diseases
- Around 3,500+ images in total
- Some classes have more samples than others (imbalance exists)
- Example:
 - Psoriasis ≈ 350 images
 - Eczema ≈ 300
 - Hair Loss ≈ 60
 - Urticaria ≈ 50



SAMPLE IMAGES

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- Images are varied in color, lighting, and skin tone
- Each class has different texture and pattern features
- Some diseases appear similar visually (e.g., eczema vs. psoriasis)
- This makes classification challenging for the model

Observation: Visual differences between diseases are subtle, requiring a deep CNN to extract detailed features.

Psoriasis pictures Lichen Planus and related diseases



Light Diseases and Disorders of Pigmentation



Actinic Keratosis Basal Cell Carcinoma and other Malignant Lesions



Melanoma Skin Cancer Nevi and Moles



PREPROCESSING

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-Resized all images to 128×128 pixels

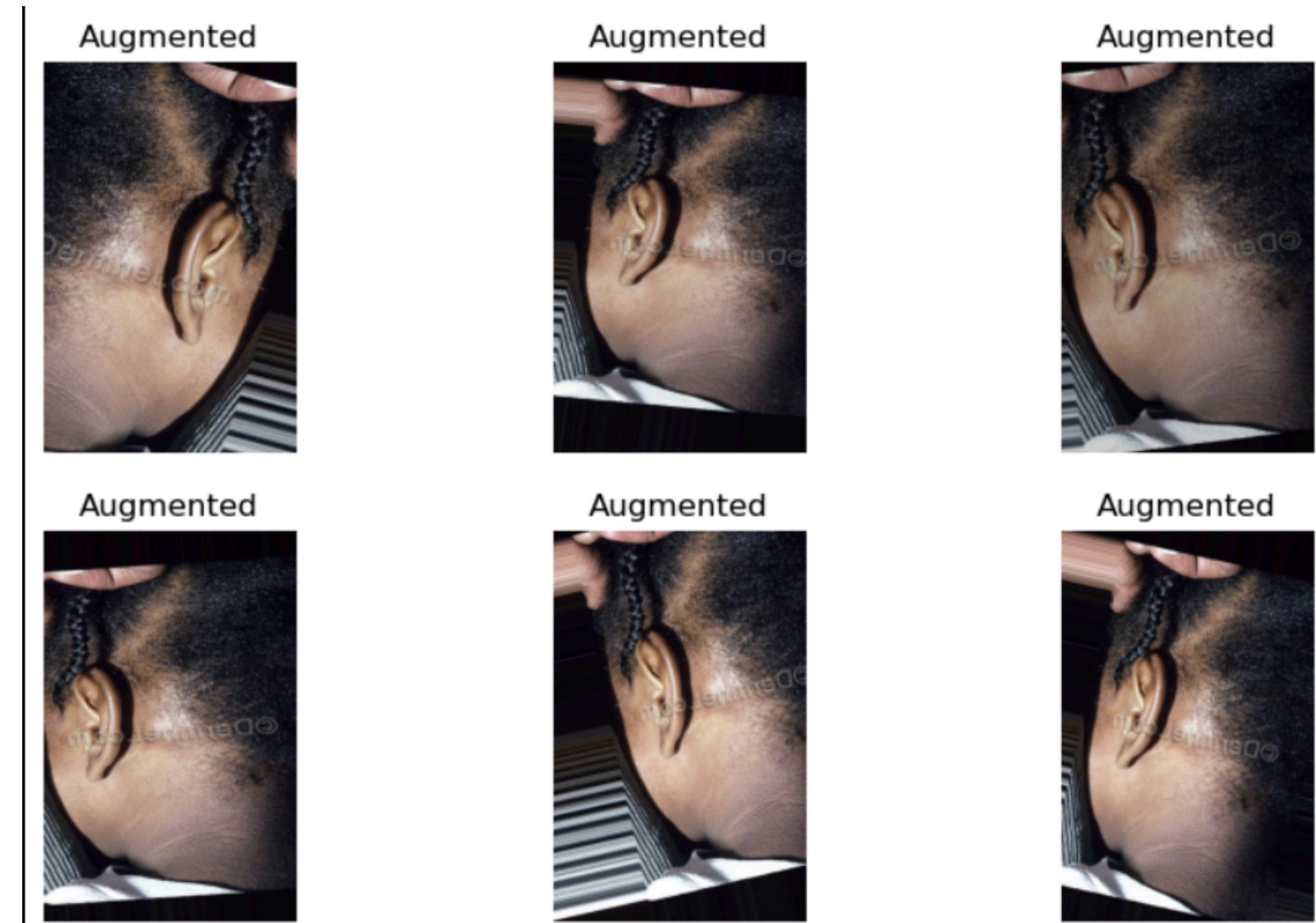
-Converted images to RGB color format

-Applied normalization (pixel values scaled between 0 and 1)

-Used data augmentation to improve generalization:

- Rotation (15–20°)
- Zoom
- Horizontal flip
- Brightness shift

-Created validation split from training set for fair evaluation



BASELINE CNN ARCHITECTURE

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-Built a simple Convolutional Neural Network (CNN)

-Layers included:

- Conv2D (32 filters, 3×3 kernel)
- MaxPooling2D (2×2)
- Conv2D (64 filters, 3×3)
- Flatten layer
- Dense (128 units, ReLU)
- Output: Dense (23 units, Softmax)

-Loss: Categorical Crossentropy

-Optimizer: Adam

-Metrics: Accuracy

Purpose: Build a simple model to establish a baseline accuracy before using pretrained networks.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
dense (Dense)	(None, 128)	11,075,712
dense_1 (Dense)	(None, 23)	2,967

Total params: 11,171,927 (42.62 MB)

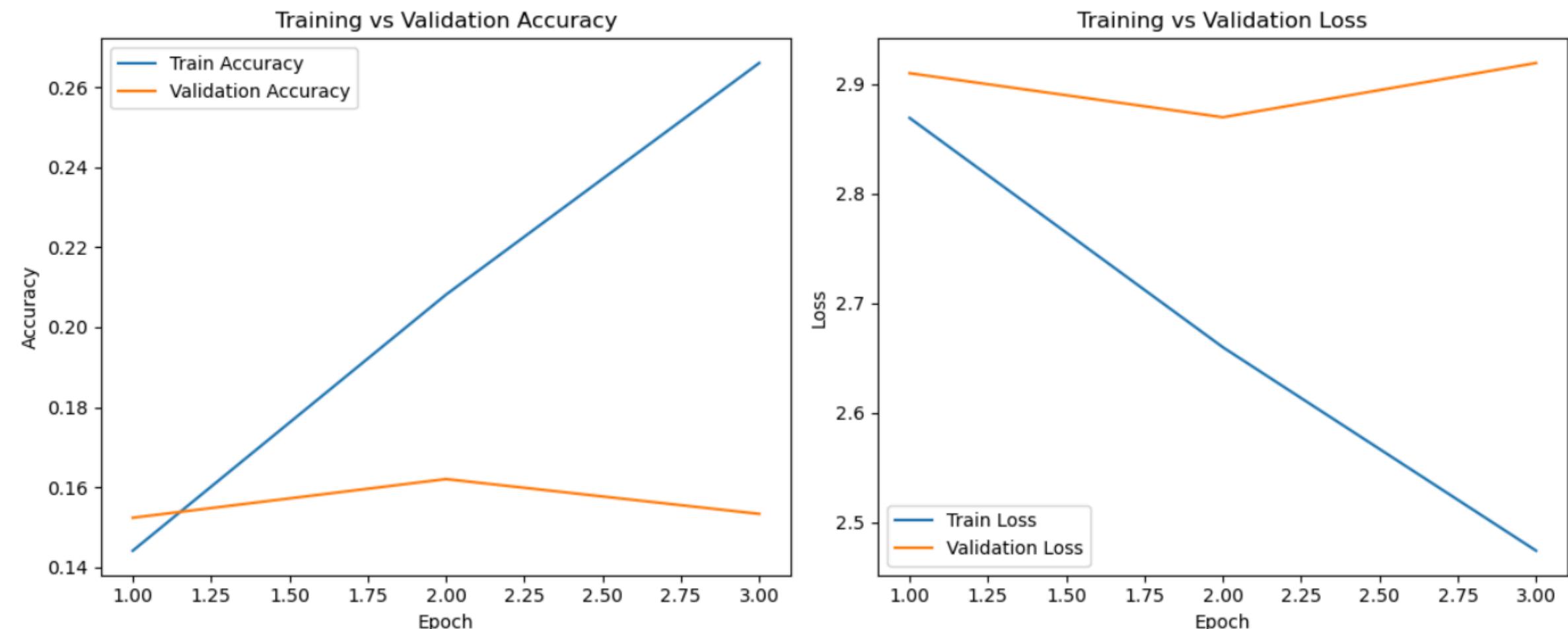
Trainable params: 11,171,927 (42.62 MB)

Non-trainable params: 0 (0.00 B)

TRAINING RESULTS (BASELINE)

- Model trained for a few epochs
- Observed quick improvement in training accuracy
- Validation accuracy increased but plateaued early
- Slight gap between training and validation → mild overfitting
- Used accuracy and loss curves to monitor progress

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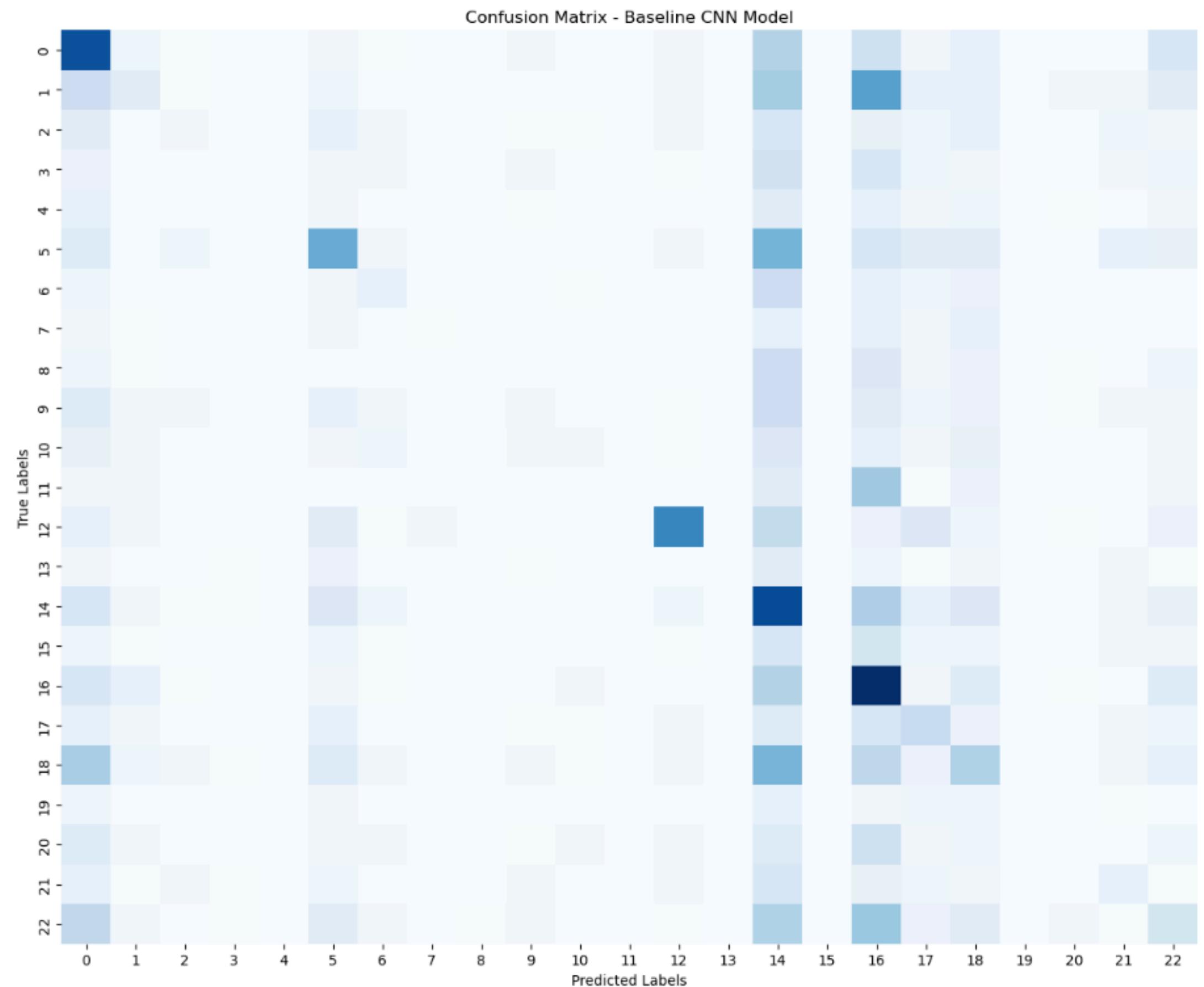


```
Epoch 1/3
390/390 ━━━━━━━━━━ 122s 310ms/step - accuracy: 0.1441 - loss: 2.8693 - val_accuracy: 0.1524 - val_loss: 2.9102
Epoch 2/3
390/390 ━━━━━━━━━━ 119s 306ms/step - accuracy: 0.2081 - loss: 2.6600 - val_accuracy: 0.1620 - val_loss: 2.8699
Epoch 3/3
390/390 ━━━━━━━━━━ 122s 312ms/step - accuracy: 0.2660 - loss: 2.4743 - val_accuracy: 0.1534 - val_loss: 2.9195
```

EVALUATION OF BASELINE MODEL

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- Evaluated on the test dataset
 - Metrics computed:
 - Accuracy
 - Precision, Recall, F1-score (per class)
 - Visualized predictions using a confusion matrix
 - Identified classes with most confusion (similar visual patterns)



TRANSFER LEARNING (PRETRAINED MODEL)

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- Used a pretrained model (VGG16, ResNet50, or MobileNetV2) trained on ImageNet
- Reused its feature extraction layers (frozen)
- Replaced the top layers with:
 - Flatten / GlobalAveragePooling
 - Dense (128, ReLU)
 - Output (Softmax, 23 classes)
- Fine-tuned top layers on the skin disease dataset
- Purpose: leverage pretrained knowledge to improve accuracy and reduce training time

Model: "sequential"

Layer (type)	Output Shape	Param #
mobilenetv2_1.00_224 (Functional)	(None, 7, 7, 1280)	2,257,984
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dense (Dense)	(None, 128)	163,968
dense_1 (Dense)	(None, 23)	2,967

Total params: 2,424,919 (9.25 MB)

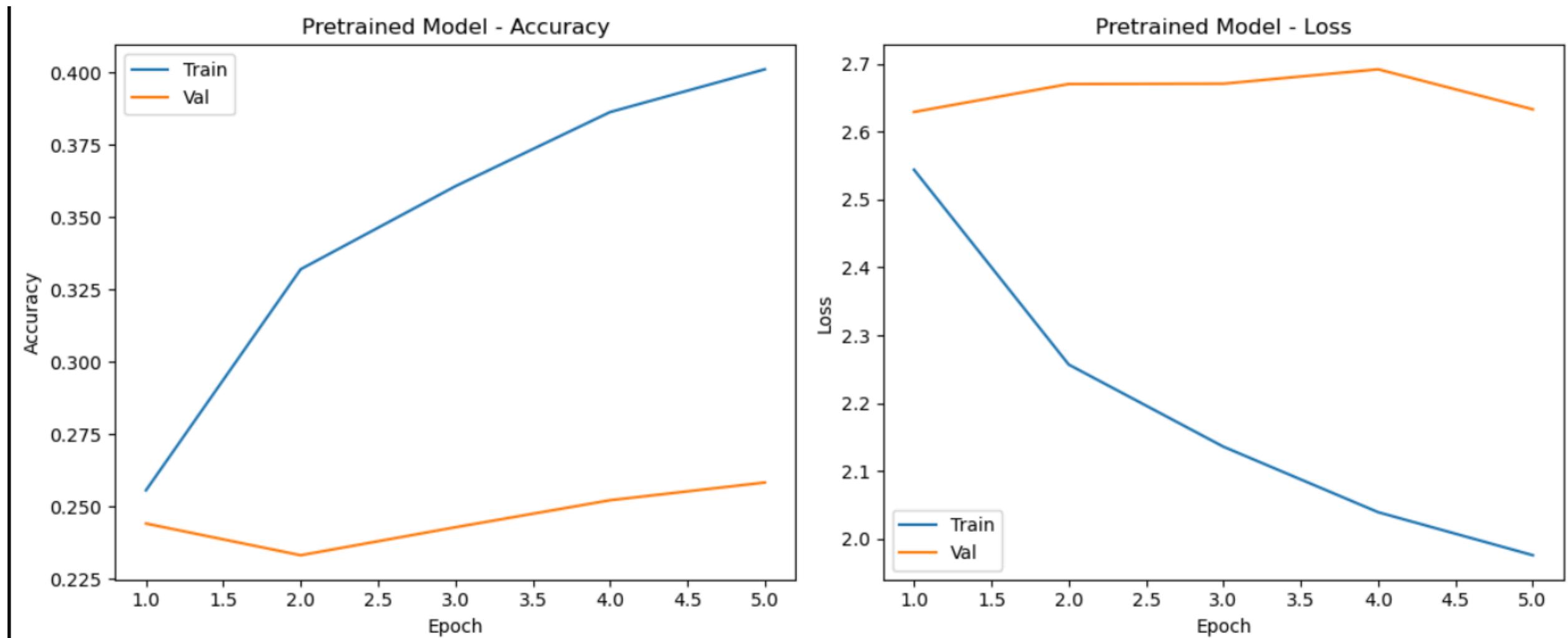
Trainable params: 166,935 (652.09 KB)

Non-trainable params: 2,257,984 (8.61 MB)

Performance Comparison

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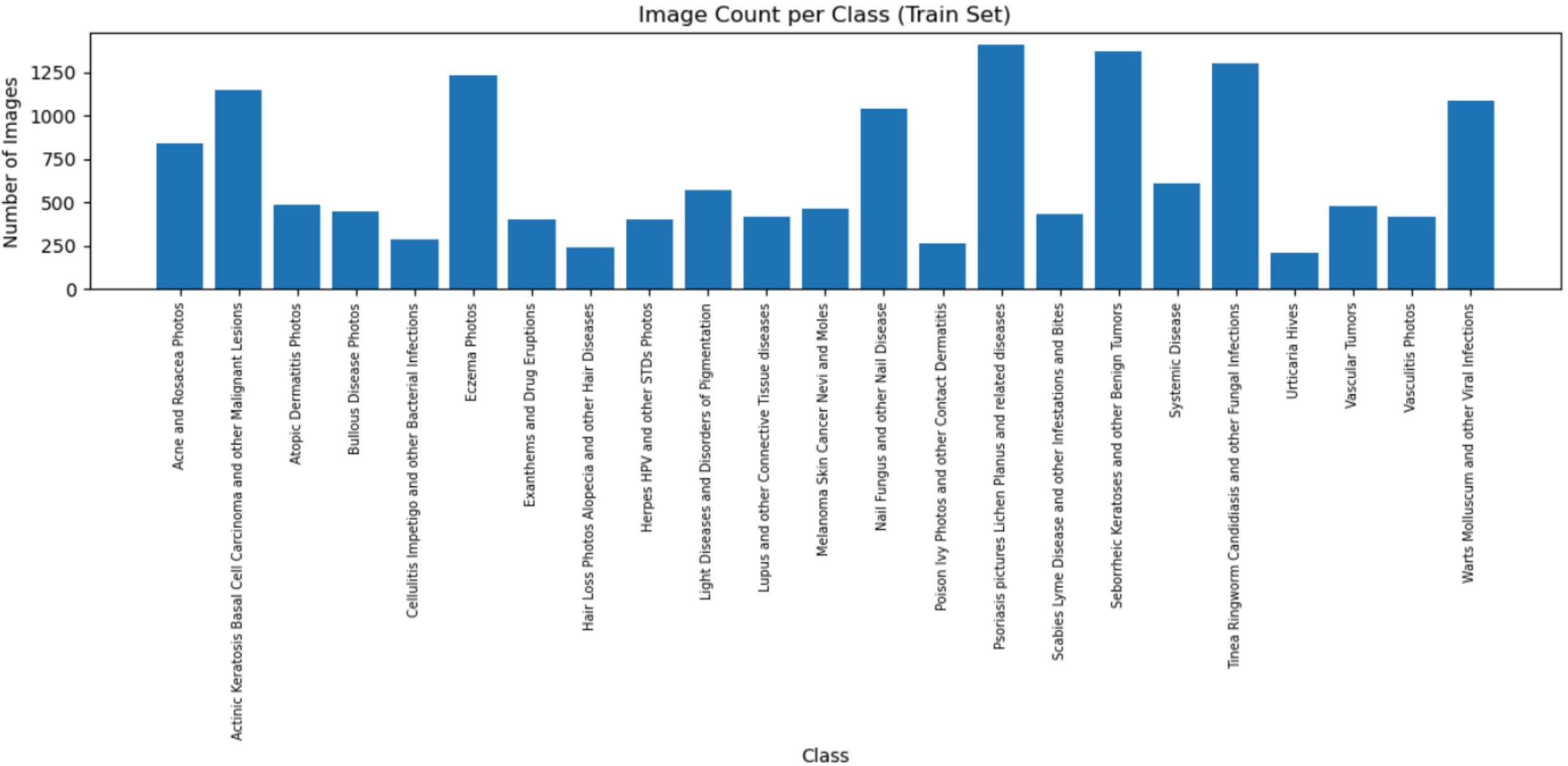
- Baseline CNN: accuracy around 25–30%, early plateau, more overfitting
- Pretrained MobileNetV2: validation accuracy $\approx 25\%$, loss decreasing steadily
- Pretrained model learns faster and is more stable
- Clear reduction in loss compared to baseline



Challenges & Learnings

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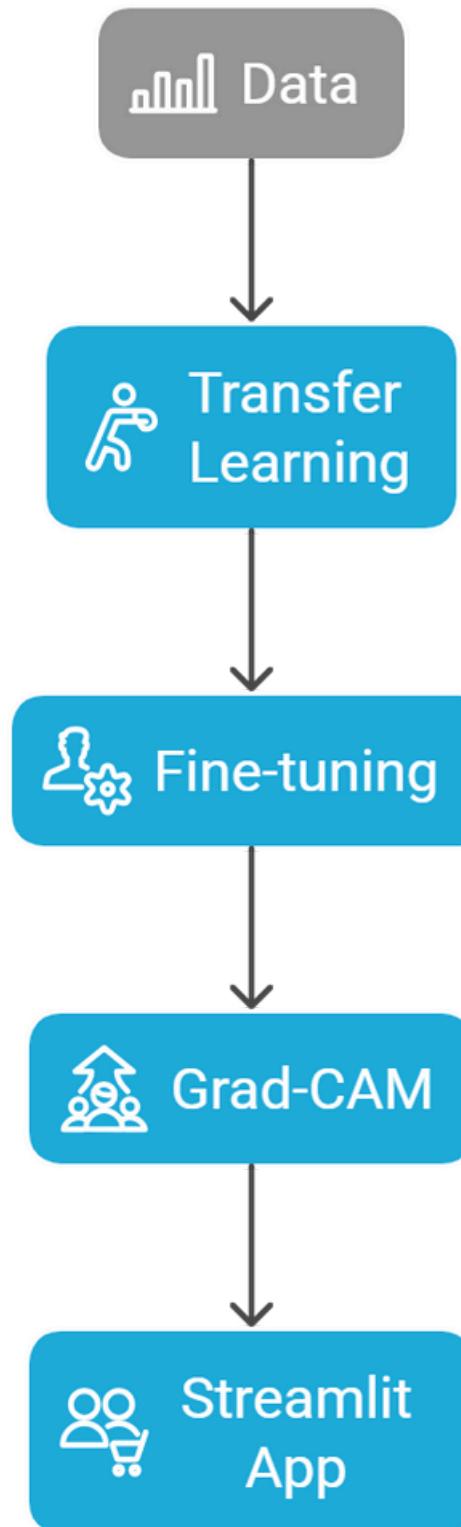
- Class imbalance across 23 classes (some under 70 images)
- Visual similarity between certain diseases causes confusion
- Variation in lighting, skin tone, zoom, and background
- Training time and GPU/CPU limits
- Transfer learning was key to reach strong performance



Future Work

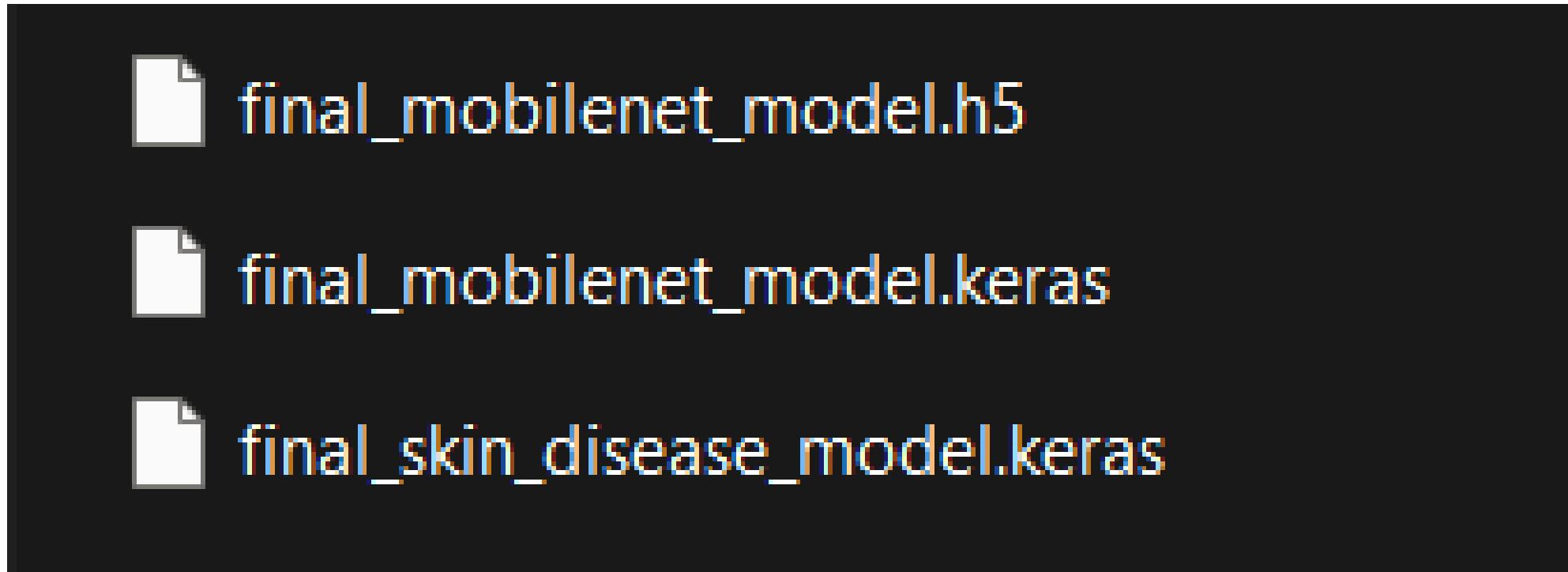
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- Balance the dataset (oversampling, class-weighted loss)
- Fine-tune deeper layers of MobileNetV2 for a few epochs
- Add stronger augmentations (color jitter, CutMix/MixUp cautiously)
- Add explainability (Grad-CAM heatmaps on predictions)
- Build a small Streamlit demo for classifying a single image
- Consider clinical validation or dermatologist feedback



Conclusion

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- Built a full multi-class image classifier on DermNet
- Baseline CNN established reference performance
- Transfer learning (MobileNetV2) clearly improved accuracy and stability
- Final model saved for reuse/deployment
- Clear next steps for fine-tuning and explainability

Thank you

