Skin diseases recognition

1. Introduction

Skin diseases affect millions of people worldwide. Early detection and accurate diagnosis of potential bite or wound, are crucial for effective treatment, yet access to dermatologist is often limited especially in Poland. An AI-powered skin disease recognition model can assist healthcare professionals and individuals in identifying skin conditions more effectively.

2. Problem Statement

The main challenge is to accurately and automatically recognize various skin diseases from images. It often happens that we notice redness, swelling or other changes on our skin and don't know what caused them. It could be an allergic reaction, an insect bite, a skin infection or another condition. In such cases, a natural question is our model. Lack of immediate access to dermatologists or medical advice often leads to unnecessary anxiety, improper self-treatment, or delayed medical intervention.

3. Target group

Our application is for anyone who doesn't know what happened to his skin. Application is designed for a wide range of users who may experience unexpected skin changes and need quick identification and advice. It is particularly useful for the general public, including individuals who notice redness, swelling, rashes, or bites and want a simple way to assess their condition without immediate medical consultation. Parents and caregivers can use the app to monitor their children's skin for allergic reactions, insect bites, or infections, while those caring for elderly family members can track age-related skin conditions. The app is also ideal for **outdoor enthusiasts and travelers** who may be exposed to insect bites, plant-related skin reactions, or sunburns in unfamiliar environments.

4. Classification model

The AI system utilizes two model architectures: a custom CNN model and a pre-trained VGG16 model, selected for their effectiveness in skin disease recognition.

The custom CNN model is designed for efficiency and flexibility. It is lightweight, ideal for mobile applications with fast training and inference. Using Grid Search, we identified the best activation function, comparing Leaky ReLU, ReLU, and SELU, and selected the optimal number of units in the dense layers, as well as the most effective dropout rates. Dropout layers were included to reduce overfitting, and normalization layers were added to stabilize training by ensuring consistent data distribution. These normalization layers help improve model convergence and accuracy.

Earlier, we developed our own custom model, but the pre-trained VGG16 model learned much faster and was significantly more accurate.

The pre-trained VGG16 model was chosen for its strong feature extraction capabilities, benefiting from the large ImageNet dataset. Fine-tuning the top layers allows the model to specialize in skin disease recognition while retaining pre-trained knowledge. The AdamW optimizer accelerates convergence and handles large datasets effectively. This model is scalable, allowing for the addition of new skin disease classes without redesigning the system.

Together, the models provide a robust solution, balancing performance, accuracy, and scalability for real-world mobile deployment.

Model: "sequential_3"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 4, 4, 512)	14,714,688
flatten_7 (Flatten)	(None, 8192)	0
batch_normalization_12 (BatchNormalization)	(None, 8192)	32,768
dense_10 (Dense)	(None, 384)	3,146,112
dropout_7 (Dropout)	(None, 384)	0
batch_normalization_13 (BatchNormalization)	(None, 384)	1,536
dense_11 (Dense)	(None, 480)	184,800
dropout_8 (Dropout)	(None, 480)	0
batch_normalization_14 (BatchNormalization)	(None, 480)	1,920
dense_12 (Dense)	(None, 480)	230,880
dropout_9 (Dropout)	(None, 480)	0
batch_normalization_15 (BatchNormalization)	(None, 480)	1,920
dense_13 (Dense)	(None, 3)	1,443

Total params: 18,316,067 (69.87 MB)

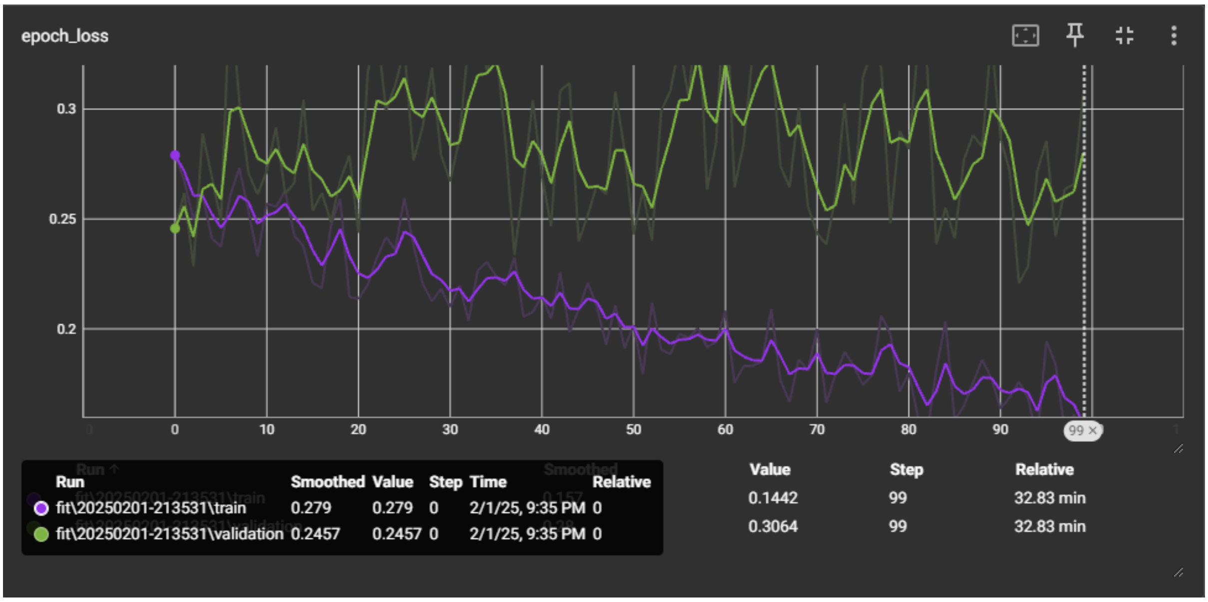
Trainable params: 3,582,307 (13.67 MB)

Non-trainable params: 14,733,760 (56.20 MB)

5. Performance highlights

Loss Performance

The graph illustrates how the model's loss evolves over training epochs.



Accuracy Performance

This chart displays the model's accuracy progression

Performance on unseen data

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7/7 ━━━━━━━━━━━━━━━━━━━━ 2s 194ms/step - accuracy: 0.9102 - loss: 0.3329
Validation Loss:  0.335456520318985
Validation Accuracy:  0.9071038365364075
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