



13 December 2025

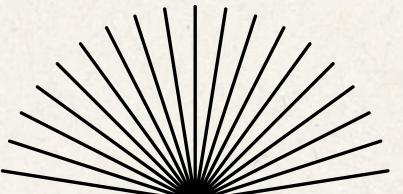
DEDICATED FOR DEEP LEARNING FINAL PROJECT

FACIAL SKIN CLASSIFICATION USING EFFICIENTNET-BO

KENNETH SUNJAYA
2702273315

NOVELLINA EDYAWATI
2702228223

STEPANUS IMANUEL
2702355574



Agenda

Introduction

Literature Review

Methodology

Implementation and Results

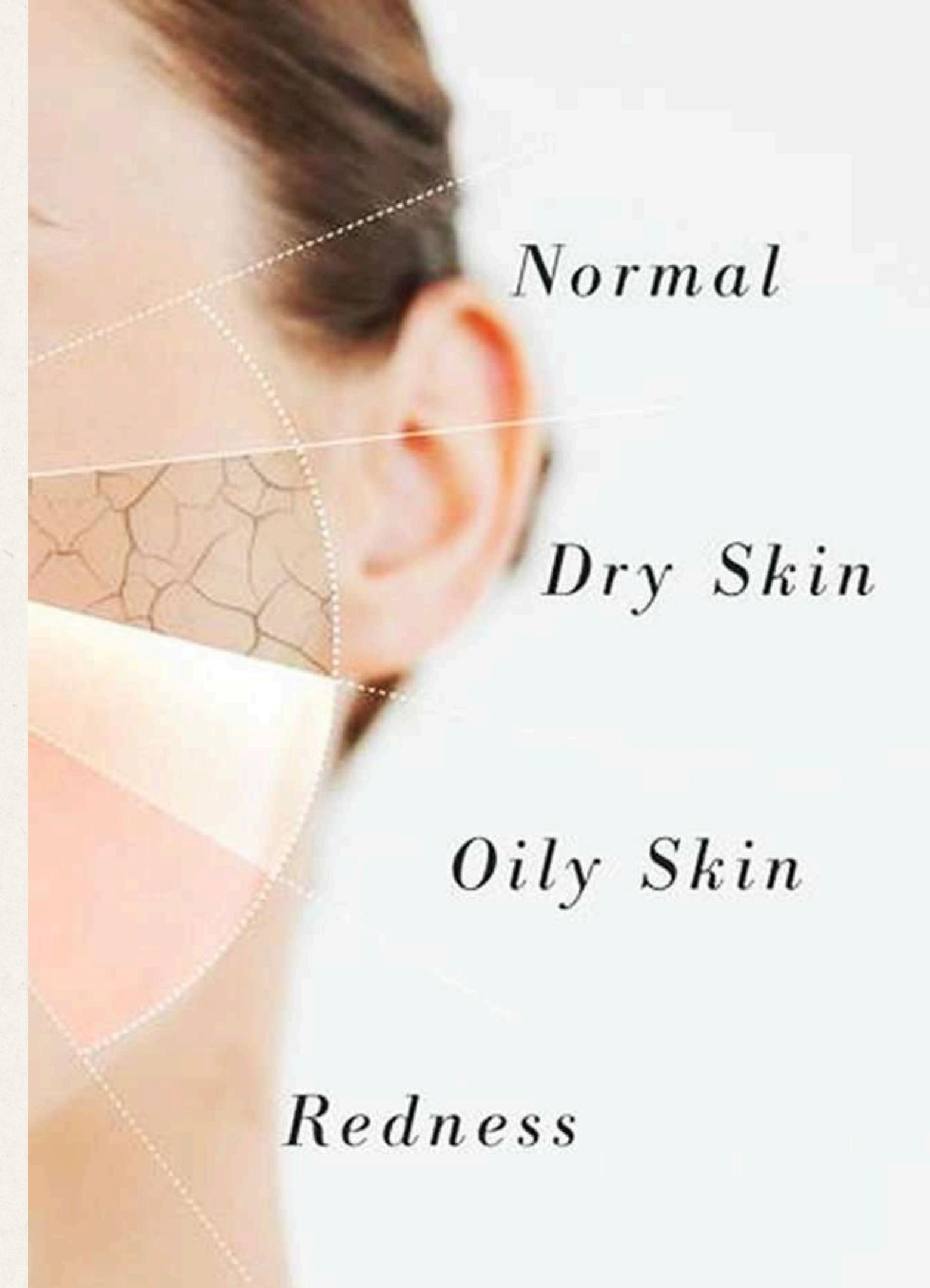
Discussion and Limitations

Conclusion and Future Work

Introduction

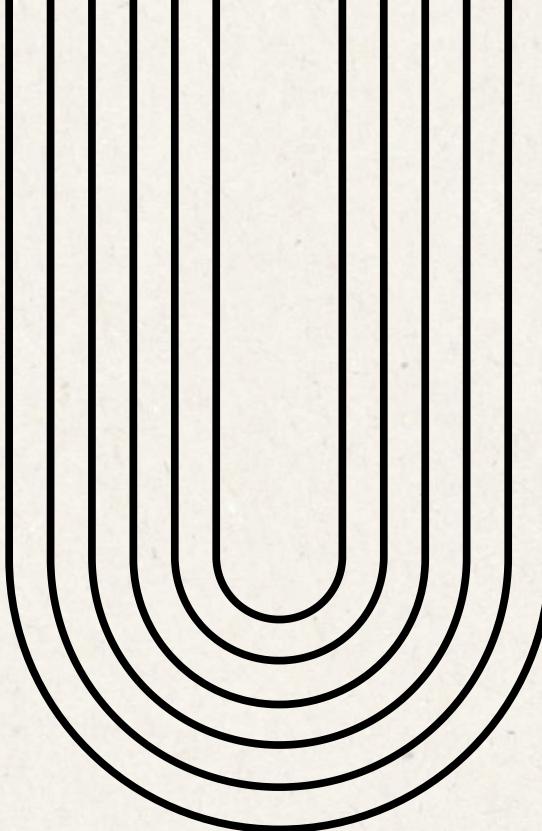
The popularity of skincare has increased across all age groups, but many individuals still lack knowledge about their actual skin type leading to inappropriate product use and potential skin problems.

Advancement in machine learning approach, particularly deep learning opens up a new opportunities for dermatological analysis. By using CNN, it can classify images by automatically learning spatial features such as texture, glossiness, pore visibility, and dryness attributes that are highly relevant for skin analysis.



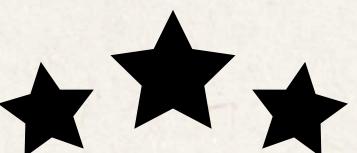
Objectives and Goals

Clarify the project's main overall objectives and goals.



Goal # 1

build a facial skin type classification model using CNNs



Goal # 2

explores the effectiveness of deep convolutional feature extraction for skin-type recognition



Goal # 3

contribute to improving the automation of dermatological analysis

Methodology

01 Dataset Preparation

Images of Dry, Normal, and Oily skin
80% training, 10% validation, 10% test

03 Training Setup

Loss Function: **CrossEntropy Loss**
SGD Optimizer
StepLR Scheduler
Batch Size: **64**
Epochs: **50**
GPU accelerated training

02 Image Preprocessing

Resize images to 224 x 224
Normalization using **ImageNet** statistics

04 Evaluation Metrics

Accuracy
Precision
Recall
F1-Score (macro)
Confusion Matrix

Samples



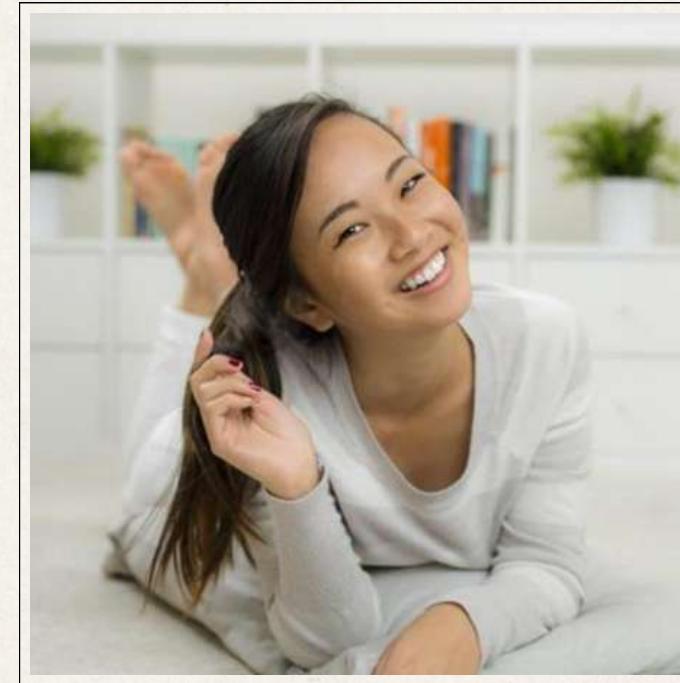
Dry

0
★



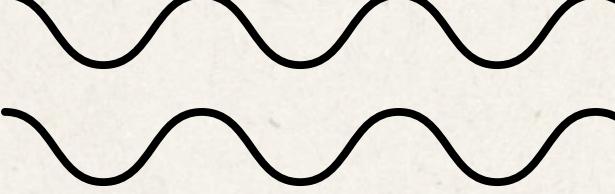
Normal

1
★



Oily

2
★



Implementation

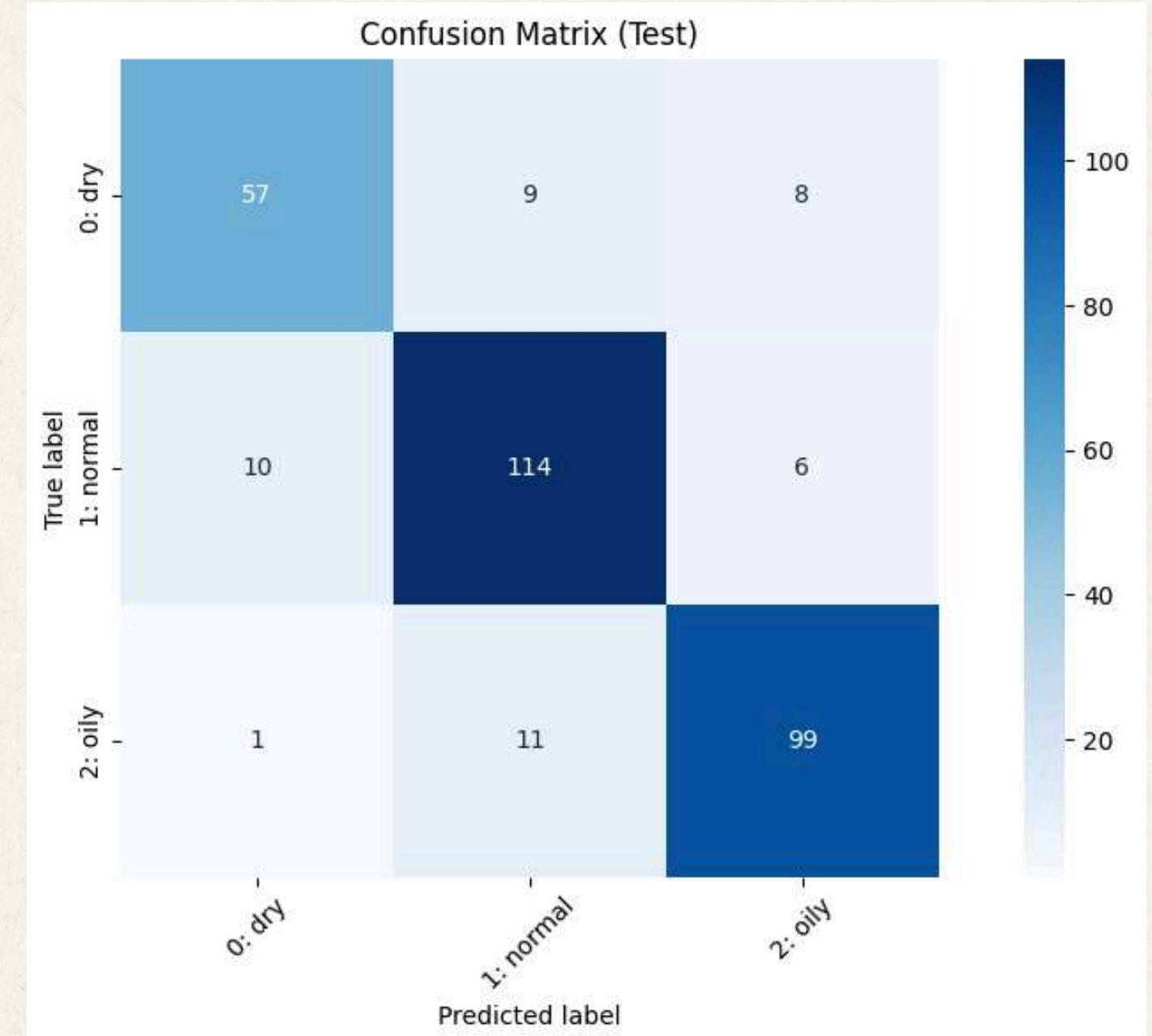
The screenshot shows a user interface for a skin type detector. On the left, there's a large input area with a placeholder "Click to upload or drag your photo here". Below this is a preview window showing a smiling woman with long brown hair. At the bottom of this section is a pink button labeled "Analyze Skin". To the right, under the heading "History", are three entries, each consisting of a small thumbnail, an ID, and a skin type label: "ID 1 dry", "ID 2 oily", and "ID 3 normal". At the very bottom of the page, outside the main container, is the text "Skin Type: dry".

- Skin-type classification system was developed and evaluated using a deep learning pipeline built on the PyTorch framework
- The EfficientNet-B0 was selected as the backbone due to its strong accuracy-efficiency trade-off.
- Pretrained ImageNet1K weights were used for transfer learning.
- The final classifier layer was modified from a 1000-class output to a 3-class fully connected layer, corresponding to the skin-type labels.
- The training was conducted for 50 epochs with an early-stopping mechanism (patience = 10) to prevent overfitting.

Result

The model achieves **85.71%** test accuracy and 85.01% macro averaged F1-score, indicates balanced performance across all three classes even with moderate class imbalance.

Confusion Matrix shows high true-positive (TP) rates for oily and normal classes



Classification Report

Class	Precision	Recall	F1-Score	Support
Dry	0.8382	0.7703	0.8028	74
Normal	0.8507	0.8769	0.8636	130
Oily	0.8761	0.8919	0.8896	111
Macro - Avg	0.8550	0.8464	0.8501	315
Weighted Avg	0.8567	0.8571	0.8565	315

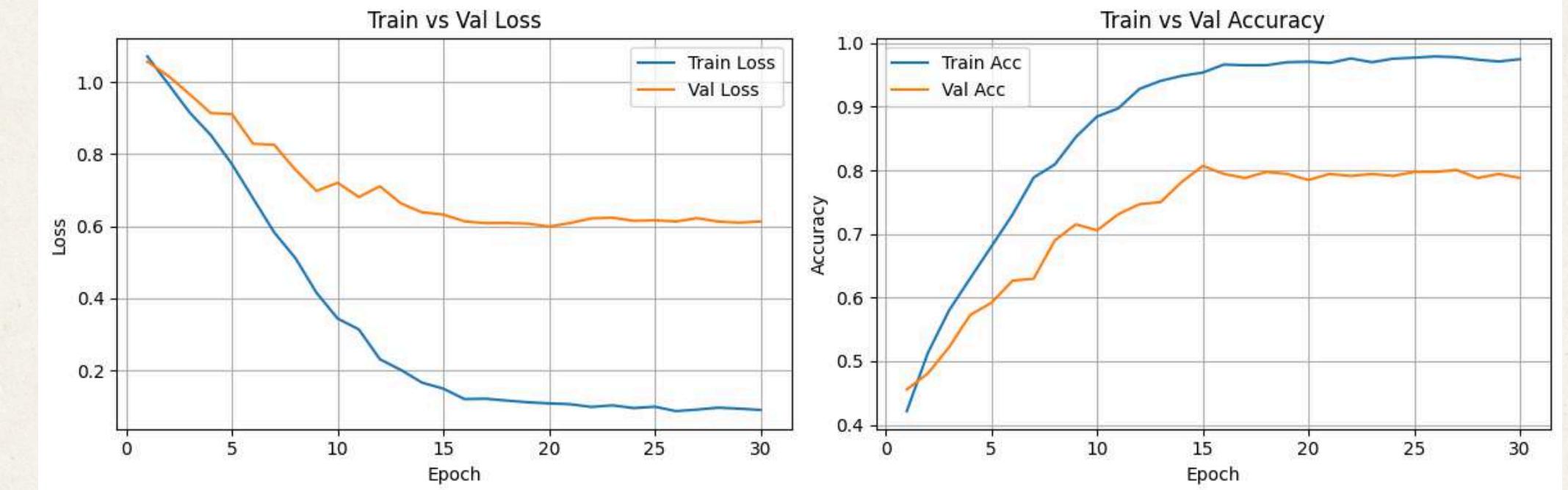
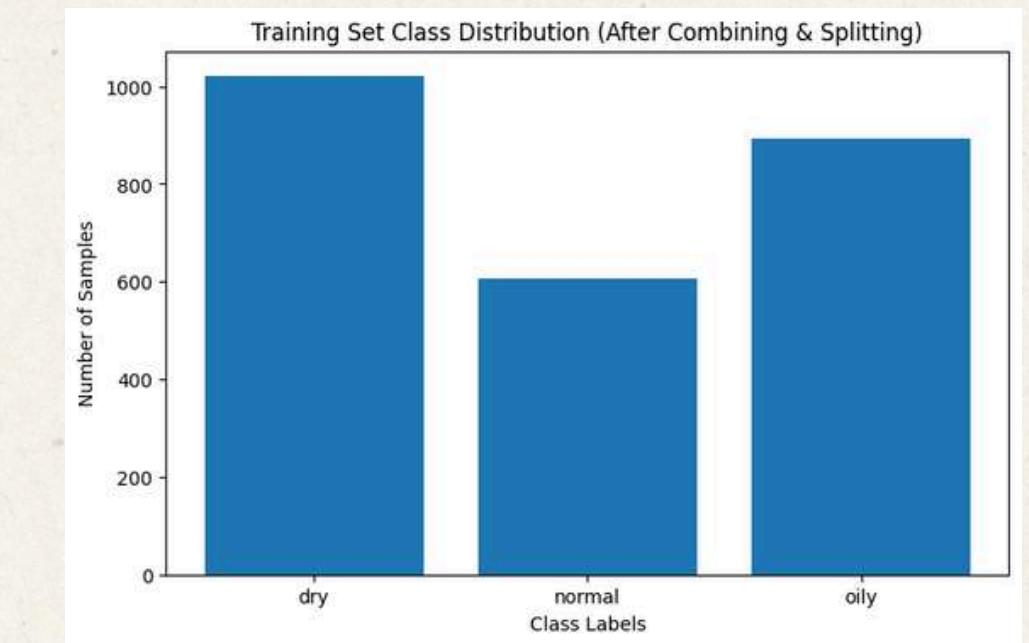
Discussion and Limitations

Fine-tuning the EfficientNet-B0 proved effective, proving that transfer learning is suitable for limited skin-type datasets.

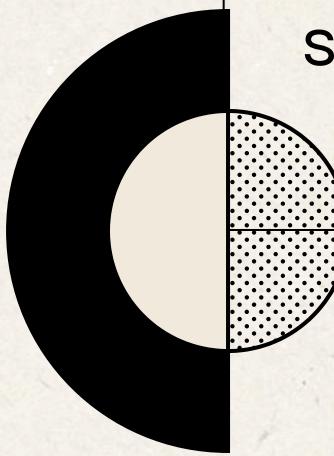
Training curves show stable convergence with no sign of severe overfitting. The early stopping strategy were effective

Limitations

- Dataset imbalance
- Only single model were tested
- Dataset inconsistencies
- Computational constraints



Challenges and Trade-off



Class imbalance	Image quality	Visually similar classes
introduced training bias and required careful handling through stratified splitting and augmentation	feature extraction more difficult and reduced model robustness	reflected in dry and normal skin

The key trade-off lies in balancing model accuracy with computational cost: higher-capacity models may improve classification performance but require more training time and resources, while lighter models offer efficiency at the expense of potential accuracy.

Conclusion and Future Work

After reconstructing the dataset split and training the model using transfer learning with data augmentation, the EfficientNet-B0 architecture achieved a test accuracy of 85.71%, demonstrating a strong accuracy-efficiency balance for automated facial skin-type assessment

The model performs strongly on normal and oily classes, although dry skin remains more difficult to classify.

Integrating clinical metadata

Exploring more advanced architectures

Expanding and improving dataset quality

Thank you
