

Skin Disease Multi-Class Classification

Deep Learning

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Problem Statement

Objective



Design and train

A lightweight Convolutional Neural Network (CNN) inspired by MobileNetv2.



Achieve

Performance comparable to the VGG16 model.



Low and efficient

Low computational cost and time efficient.

Dataset characteristics

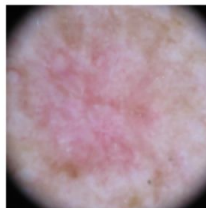
Multiple Skin Disease Image Dataset.

Limitations

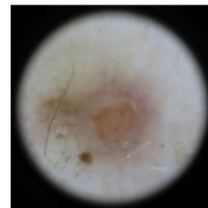
Small dataset: 4109 images

Noise: hair, microscope lens borders and marker artifacts.

Actinic Keratosis
(Precancerous)



Basal Cell Carcinoma
(Cancerous)



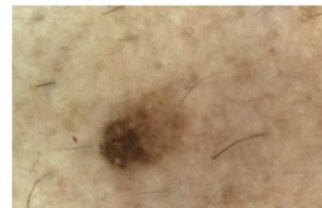
Dermatofibroma
(Benign or non-cancerous lesions)



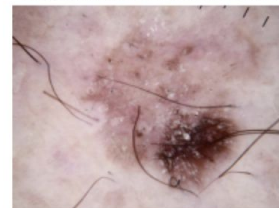
Melanoma
(Cancerous)



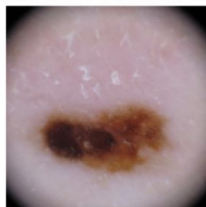
Nevus
(Benign or non-cancerous lesions)



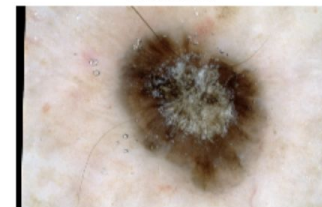
Pigmented Benign Keratosis
(Benign or non-cancerous lesions)



Seborrheic Keratosis
(Benign or non-cancerous lesions)



Squamous Cell Carcinoma
(Cancerous)

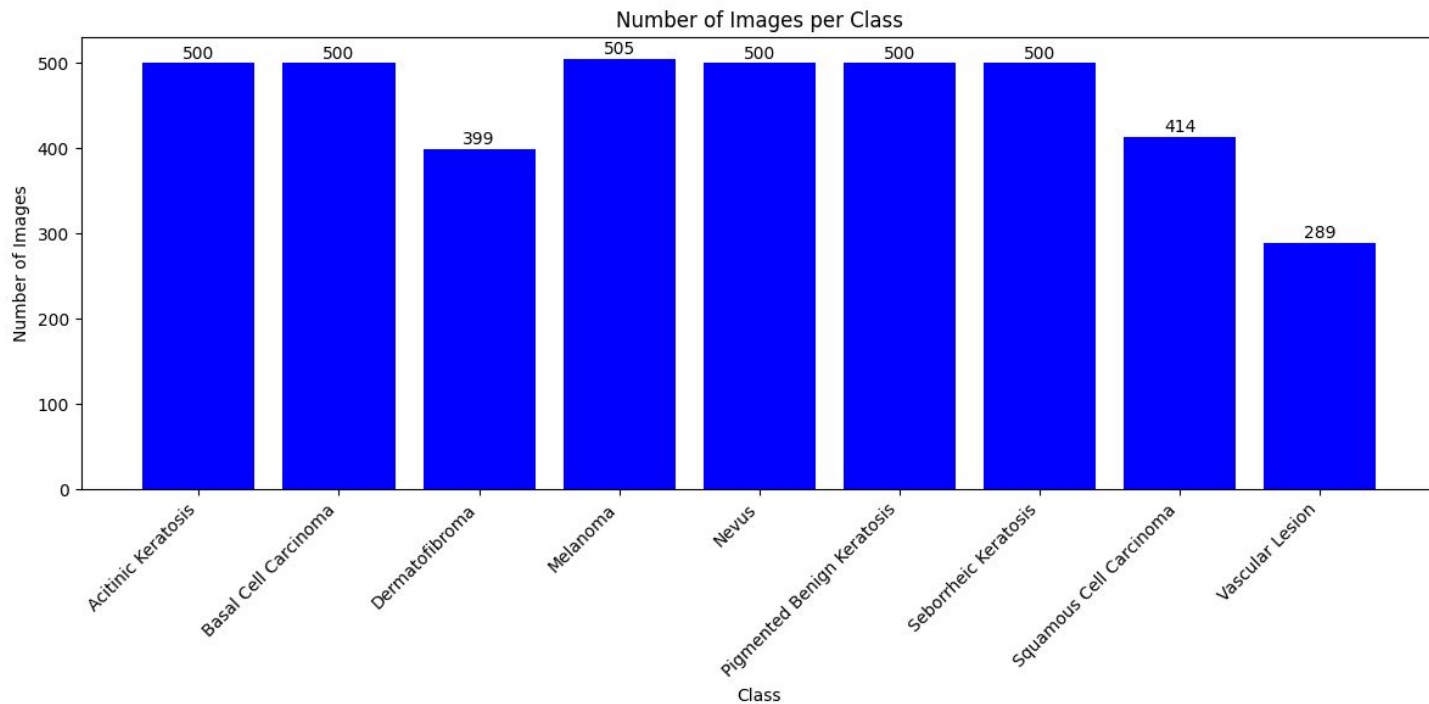


Vascular Lesion
(Benign or non-cancerous lesions)



Dataset characteristics

Distribution



02

State-of-art

State of the Art



State - of - the - art skin disease classification: a review of deep learning models

- Average an accuracy of 86.20% achieved by different deep learning models and data.



Best model using the same dataset: VGG16 89% of accuracy

- Transfer learning with a VGG16 model with pre-trained ImageNet weights.
- >20M parameters.

03

MyEfficientCNN

Architecture

Inspired by MobileNetV2 MyEfficientCNN vs

MobileNetv2

- # Inverted residual blocks → # channels, parameters

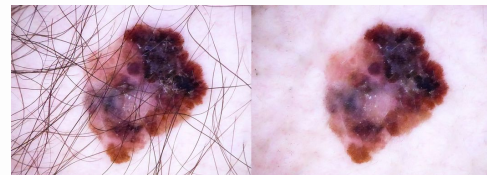
Model structure

- Uses inverted residuals, depthwise separable convolutions, and linear bottlenecks

Experiments

Training approach

- Previous knowledge: good performance on simple data MNIST
- Performance in complex data?
 - Worse performance (1.5 loss, 50.7% accuracy)
 - Test with data pre-processing (Dull Razor algorithm) →
- Data augmentation: $\pm 15^\circ$ rotation, flipping
 - + Generalization
 - + Robustness
 - Diverse data
- Hyperparameters



Experiments

Test

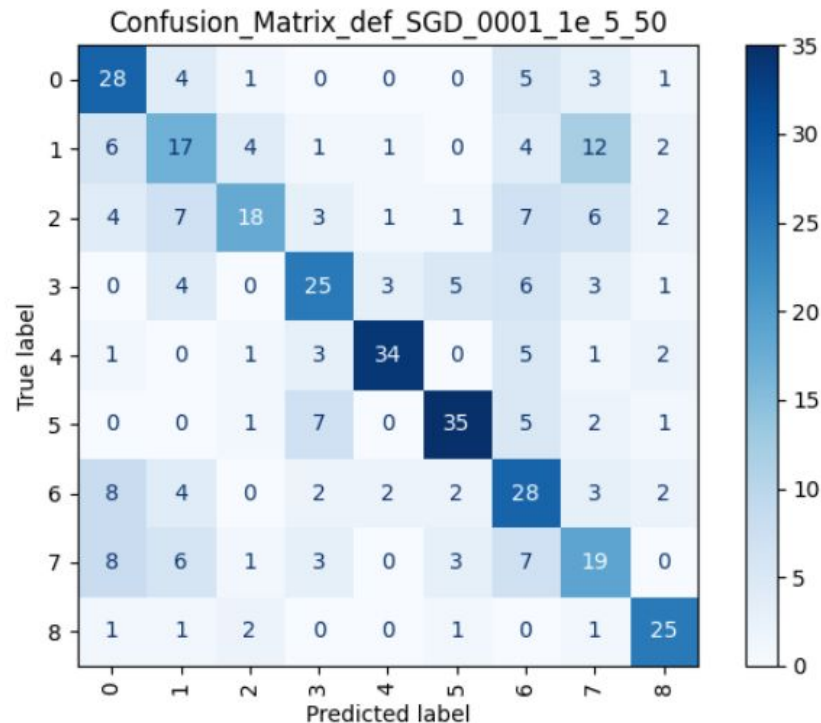
Results test set:

Loss: 1.26

Recall: 56.63%

Accuracy: 55.58%

Confusion mtx: observe label predictions against labels of each class



04

Transfer Learning

Transfer Learning Methodology

MobileNetV2

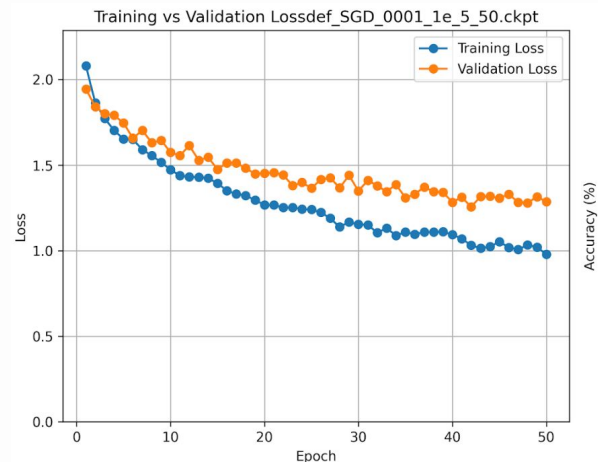
- Pretrained on ImageNet (1,000 classes).
- Lightweight model: ~2M parameters vs ~20M in VGG.

Why we choose it?

- Custom model are not strong enough
- Limited input data

Data adaptation

- Normalized with ImageNet mean and std.



Experiments

Training approach

- Input size: 224x224
- Number of total parameters: 2,235,401
- Feature Extraction
 - **Validation Loss:** 1.30, **Accuracy:** 57.32%, **Recall:** 56.82
 - **Trainable variables:** 11,529
- Fine Tuning (Unfreezing the last layers)
 - **Validation Loss:** 0.82, **Accuracy:** 73.41%, **Recall:** 73.03%
 - **Trainable variables:** 1,996,041

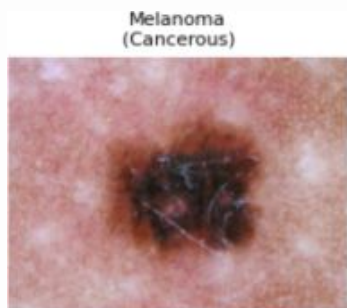
Experiments

Test

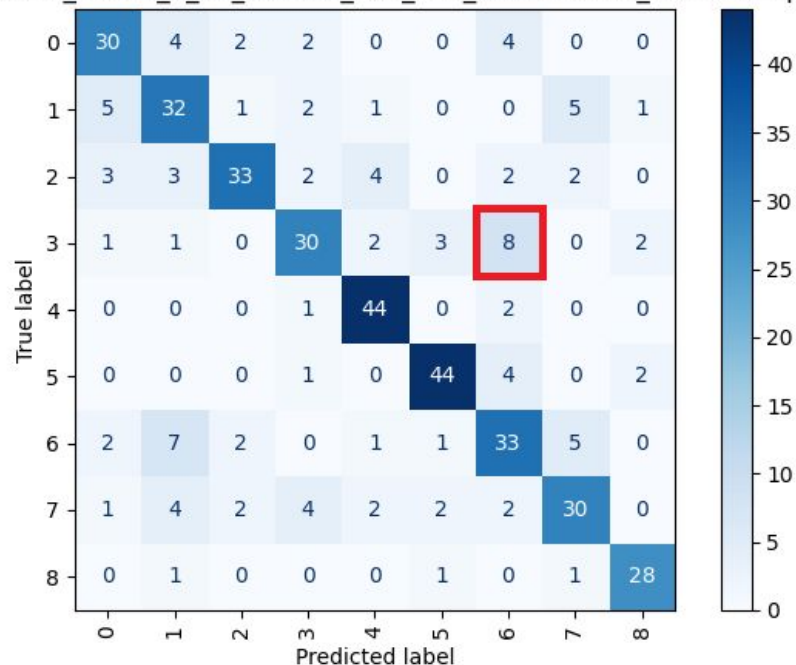
Results test set:

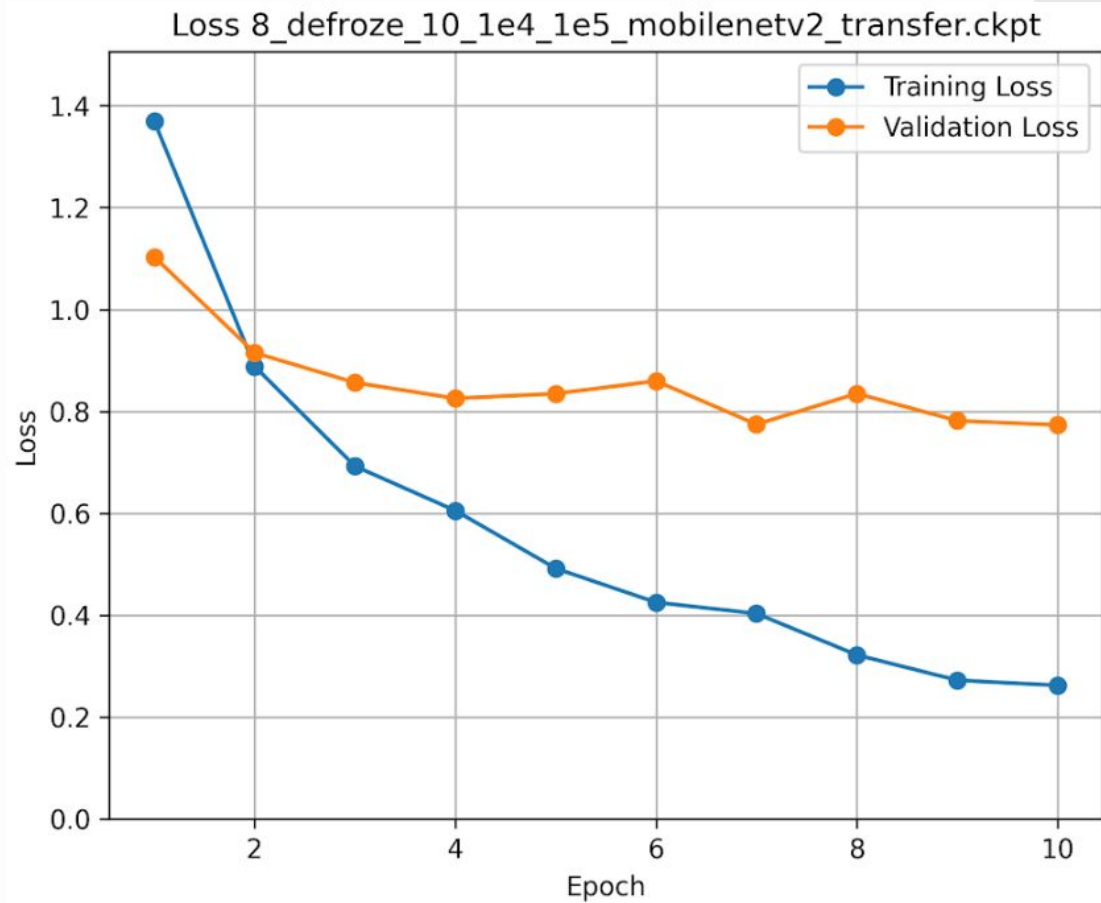
Loss: 0.8205, **Accuracy:** 73.79%,

Recall: 74.38%



Confusion_Matrix_8_32_defroze_1e4_1e5_mobilenetv2_transfer.ckpt





05

Conclusions

What worked?

- Transfer learning improves performance over our model.
- 2M param close results to VGG16 (20.5M).

What didn't work?

- Did not achieve the VGG16 results.
- Obtain acceptable results with MyEfficientCNN.

Future work:

- Image processing techniques: segmentation, color spaces.
- Cross validation: builds a robust model.

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References

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THANK YOU



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