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# Enhancing Skin Disease Classification with Depthwise Separable Inception Network

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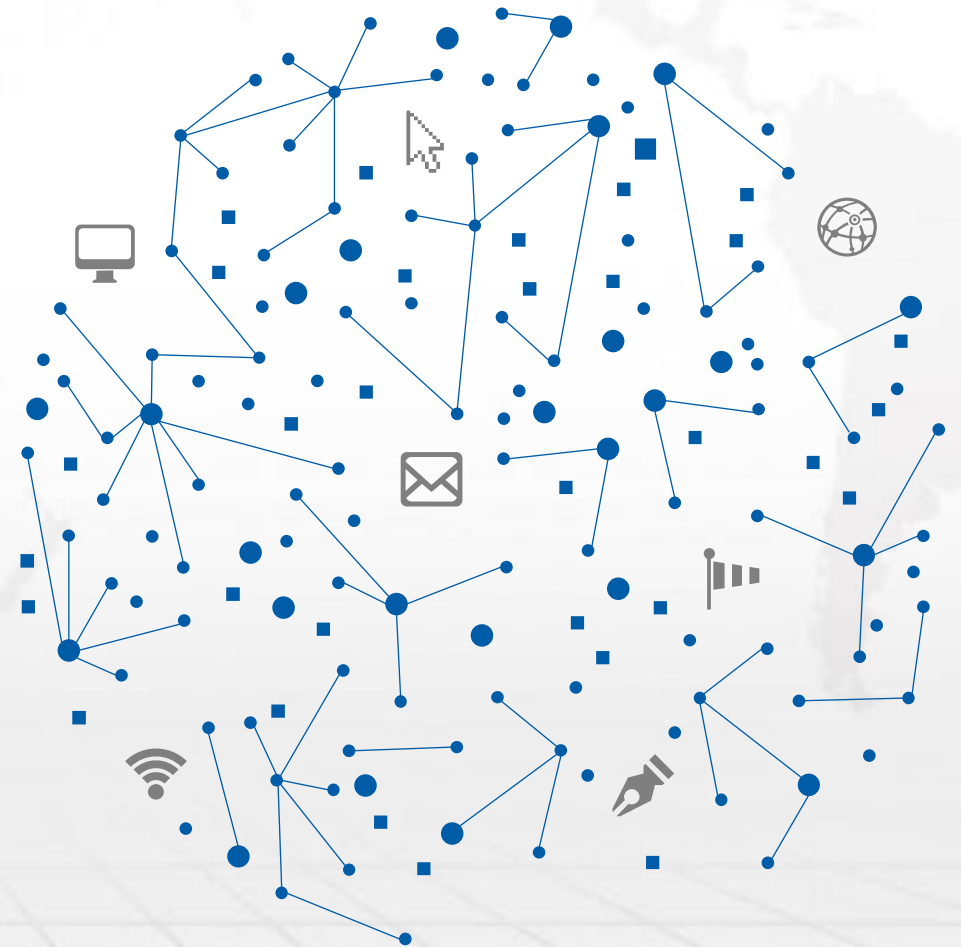


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# Introduction

Aim, objectives

# Introduction-Aim

## Problem

- The American Cancer Society estimates that in 2024, about 100,640 new melanoma cases will be diagnosed in the United States, and about 8,290 people will die from melanoma.[1]
- Traditional skin disease classification relies on medical experience by doctors. Through effective, this approach is time-consuming and dependent on varying skill levels.

## Solution

- Deep learning with convolutional neural networks (CNN) has been widely used for image classification, including skin diseases.
- The use of inception model and depthwise separable convolution can improve the performance.

# Introduction-Objectives

Dataset download and process



01

02



Model implementation

Model training



03

04



Model evaluation

Hyperparameter adjustment



05

06



Build GUI of best model

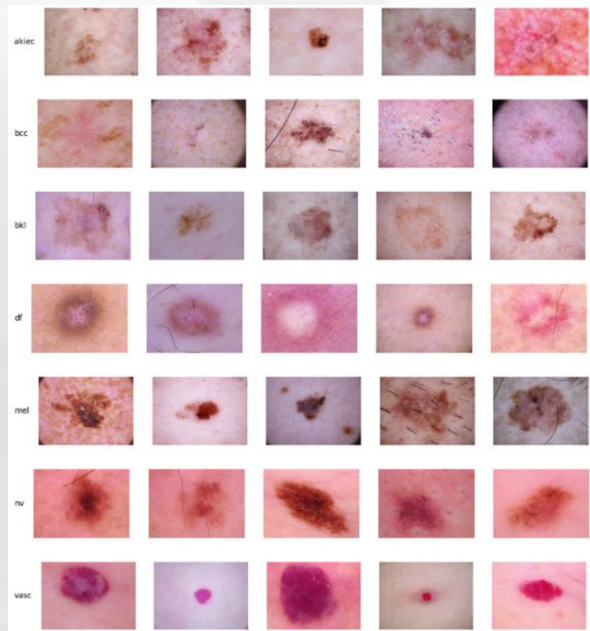


# Methodology

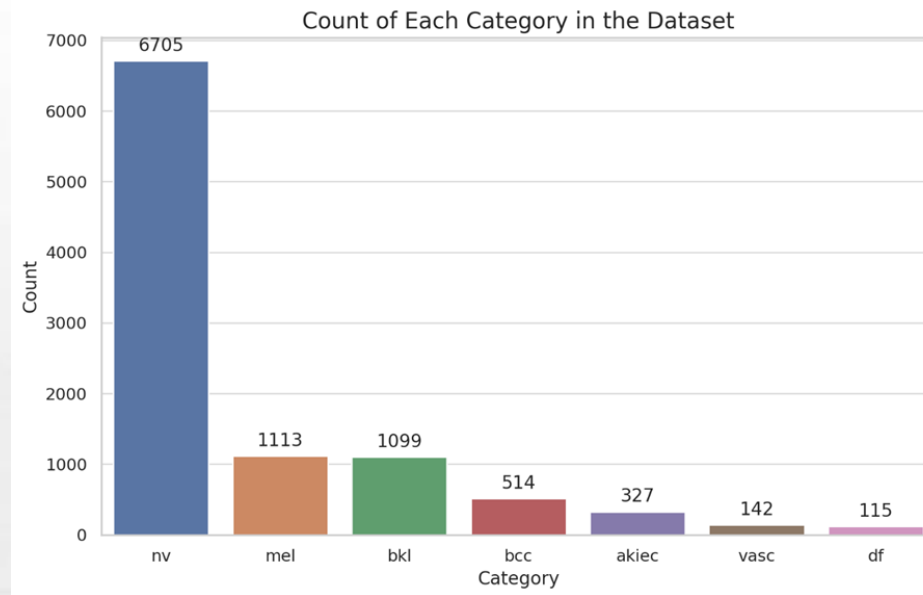
Dataset, model

# Methodology-dataset

The HAM10000[2] "Human Against Machine with 10000 training images" dataset, is a large collection of 7 classes of skin disease images.



**HAM10000**



**Number of each class**

**nv** - Melanocytic Nevi  
**mel** - Melanoma  
**bkl** - Benign Keratosis-like Lesions  
**bcc** - Basal Cell Carcinoma  
**vasc** - Vascular Lesions  
**akiec** - Actinic Keratoses and Intraepithelial Carcinoma  
**df** - Dermatofibroma

# Methodology-dataset

80%

## Train set

Used to train the model

10%

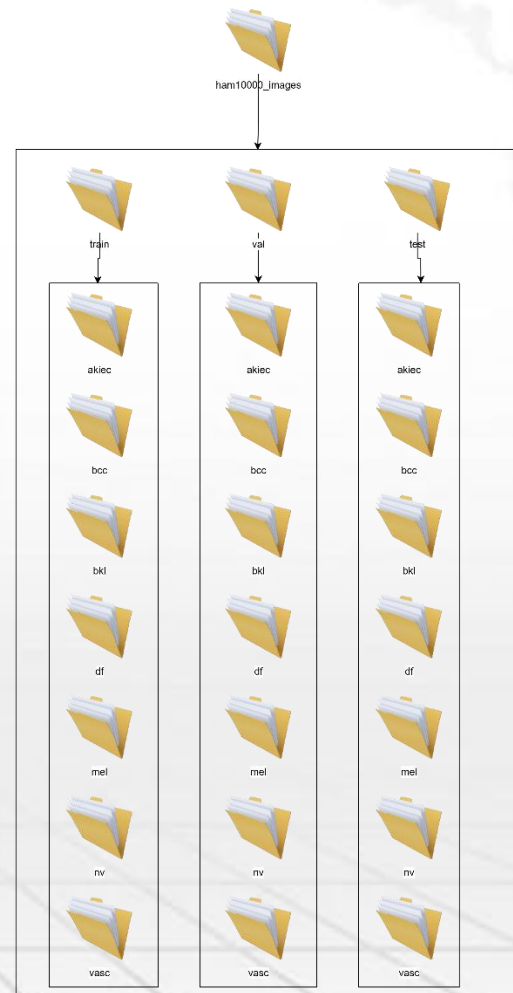
## Validation set

Used to adjust model hyperparameters

10%

## Test set

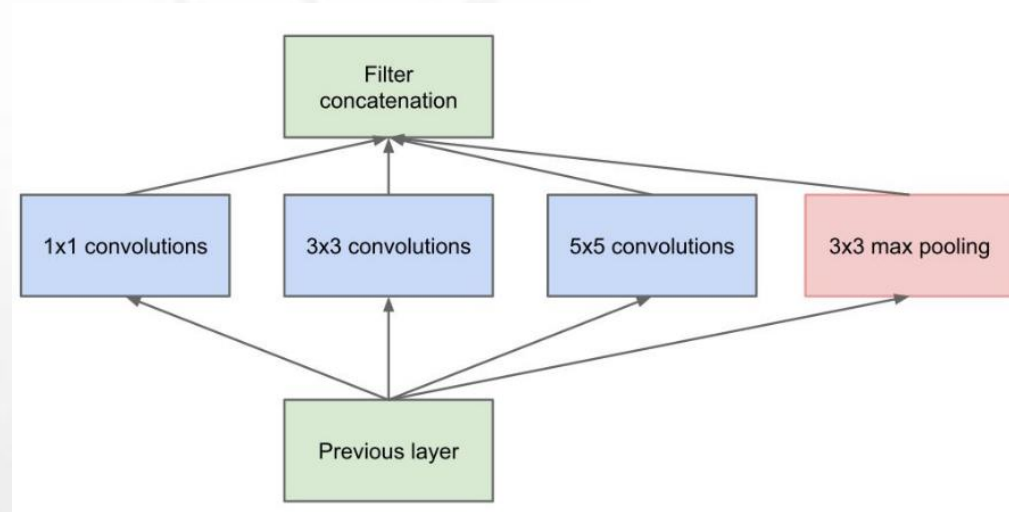
Used to evaluate models





# Methodology-model

## Inception



The inception[3]

The core innovation of the Inception model is the Inception module, which extracts image features through parallel multi-scale convolution operations. Each Inception module includes convolutional filters of different sizes (1x1, 3x3, 5x5) and pooling operations, allowing it to capture features at multiple scales and combine them.

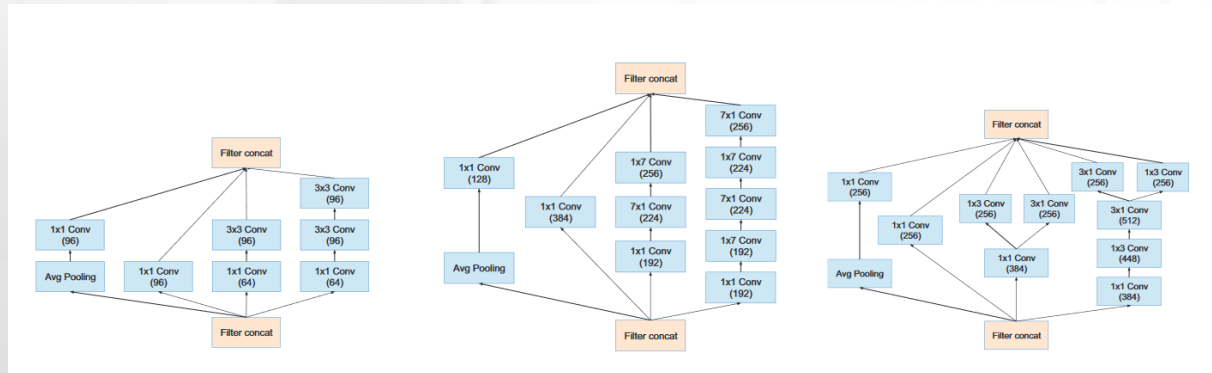
### Benefits:

Multi-scale processing can retain the information in the image to the greatest extent, avoid information loss, and improve the overall performance of the model.

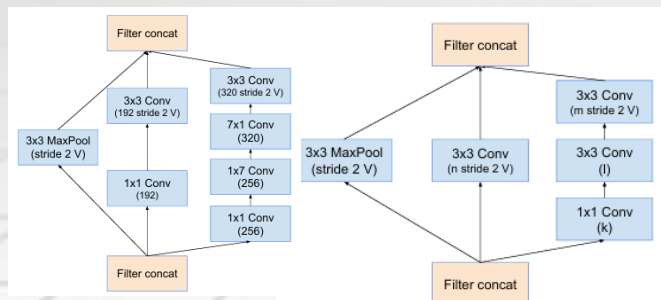
# Methodology-model

## Inception V4

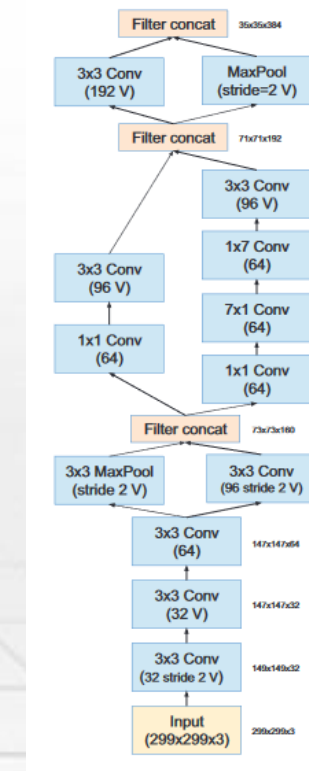
It is improved and optimized on the basis of Inception, mainly introducing more modules and structures to improve the accuracy and efficiency of the model.



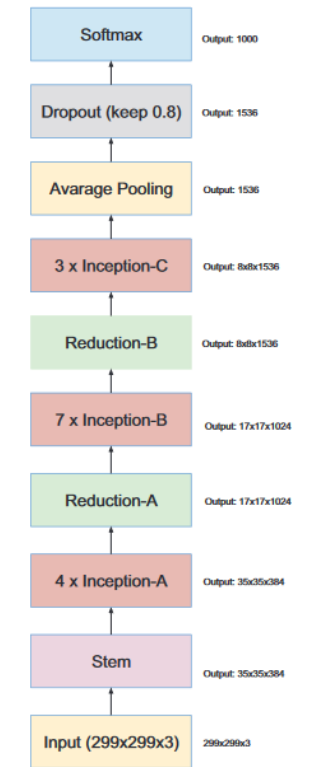
Inception block A,B,C in Inception V4[4]



Reduction A(left),B(right) in Inception V4[4]



Stem[4]



overall structure[4]

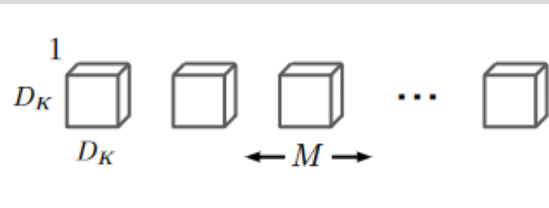
# Methodology-model

## Depthwise separable convolution

Depthwise Convolution divide into two independent operations: Depthwise Convolution and Pointwise Convolution.

### Depthwise convolution

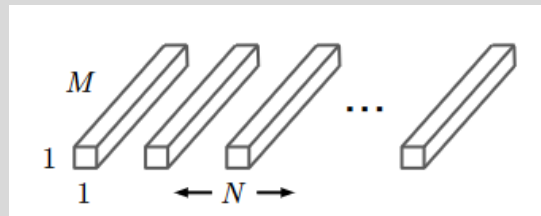
Depthwise convolution applies one separate kernel for each input channel, rather than applying the same kernel to all channels as standard convolution does.



Depthwise convolution[5]

### Pointwise convolution

Point-by-point convolution uses the  $1 \times 1$  convolution kernel to linearly combine the output of the depthwise convolution, a step that connects all channels.



Pointwise convolution[5]

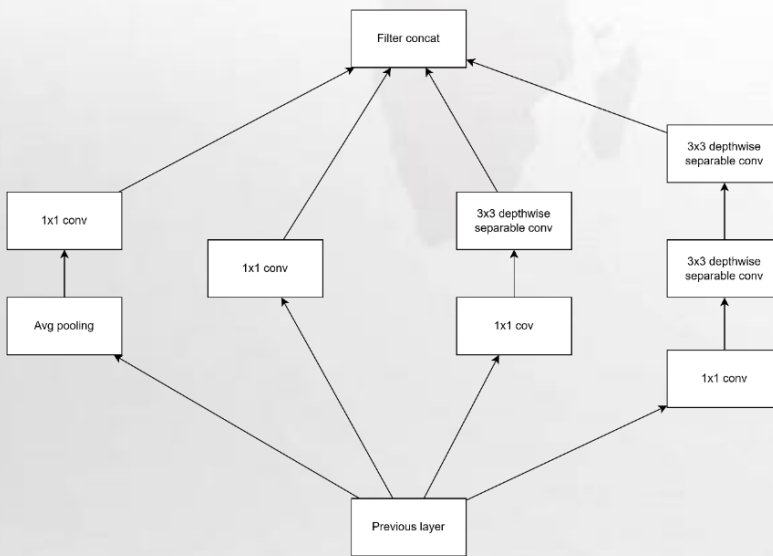
### Depthwise separable convolution

Benefits:

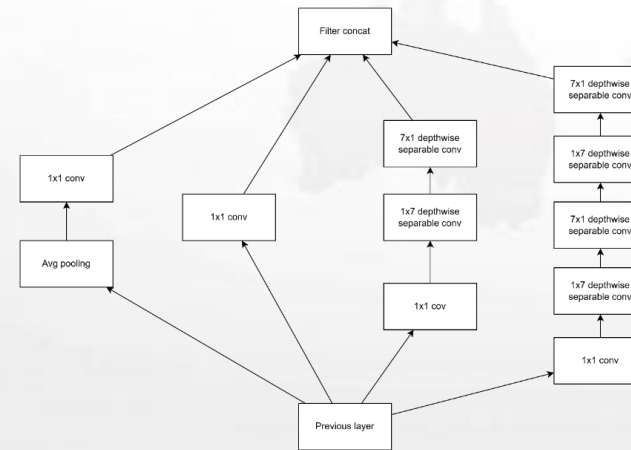
The combination of depthwise convolution and pointwise convolution significantly reduces the amount of computation and the number of parameters. On the situation of maintaining the performance of the model, the computational efficiency is improved

# Methodology-model

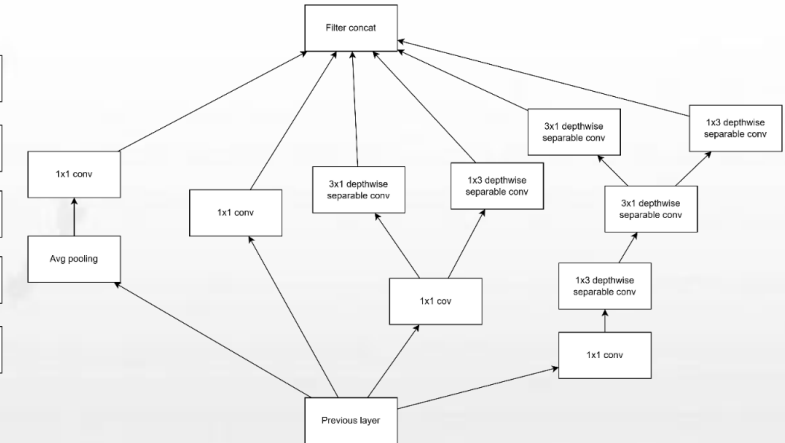
## Combine of inceptionV4 and depthwise separable



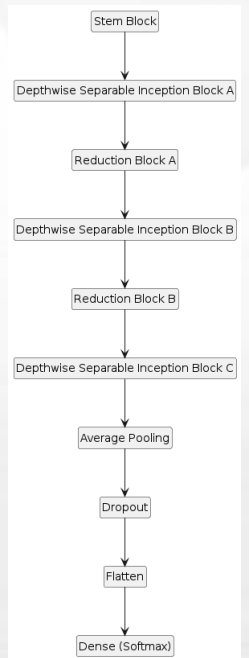
Depthwise separable inception block A



Depthwise separable inception block B



Depthwise separable inception block C



Overall structure of depthwise separable inception model

Combine of benefit of two of them, improve the accuracy and efficiency



# Implementation & Results

# Implementation & Results

Software and hardware for build the model

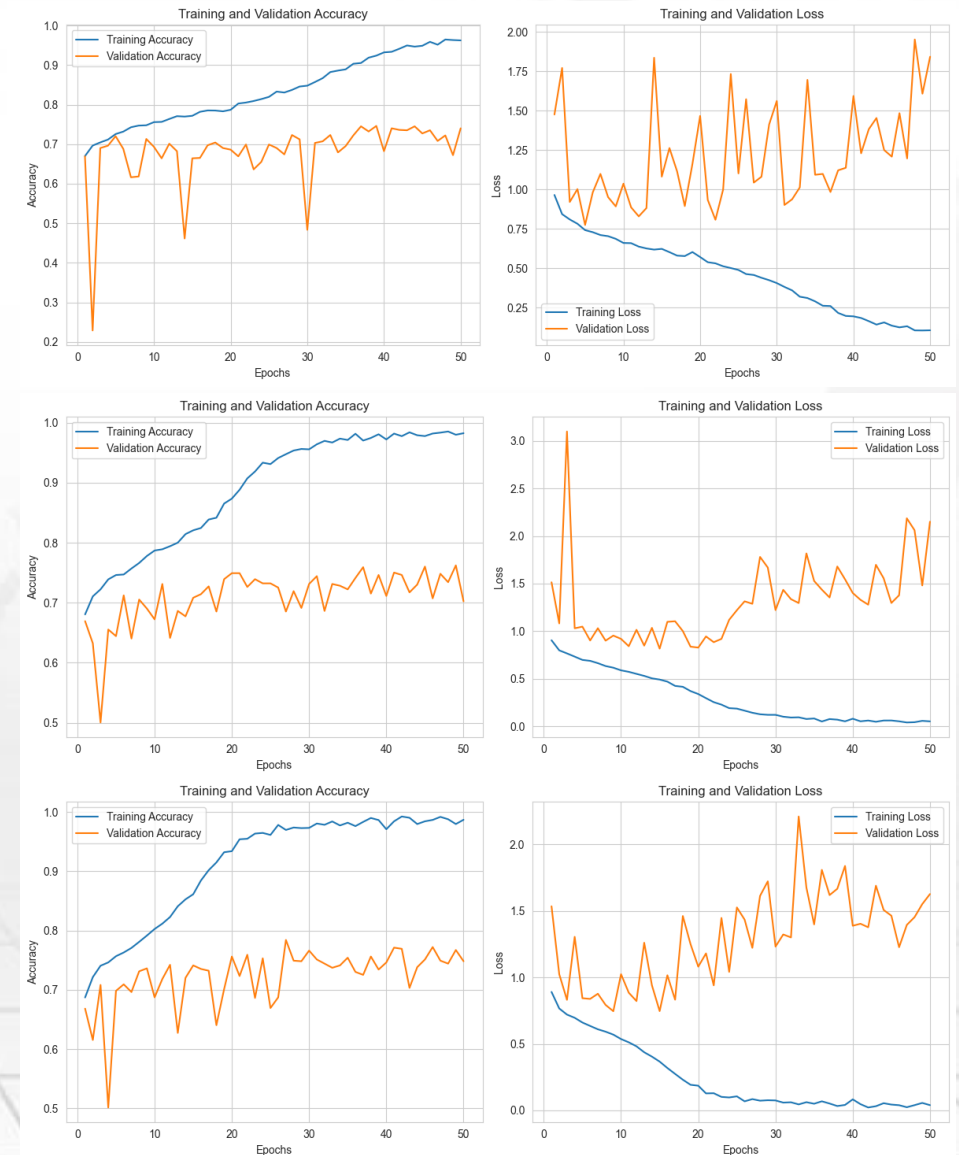
Software	Framework	TensorFlow
	Language	Python
	Libraries	Numpy, Pandas, Matplotlib, sklearn
	Version management plan	Git repository
Hardware	Central processing unit(CPU)	Intel(R) Core(TM) i7-13700KF CPU @ 3.40GHz
	Graphic Processing Unit(GPU)	NVIDIA GeForce RTX 4090

# Implementation & Results

For optimization and training control, the model utilizes an Adam optimizer at the learning rate of 0.001, categorical crossentropy as the loss function.

Compare of different number of inception block

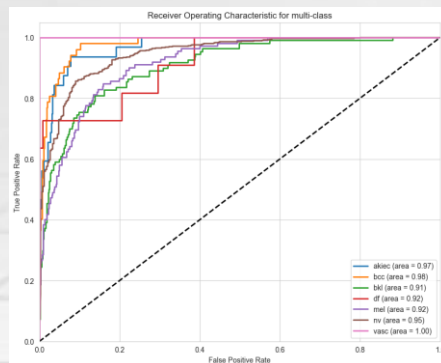
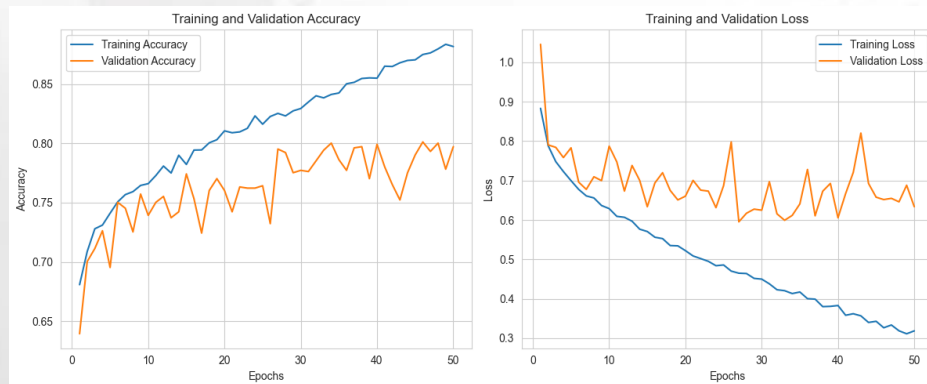
Depthwise Separable Inception Block A	Depthwise Separable Inception Block B	Depthwise Separable Inception Block C	Test Accuracy (%)
4	7	3	72%
2	4	1	73%
1	1	1	75%





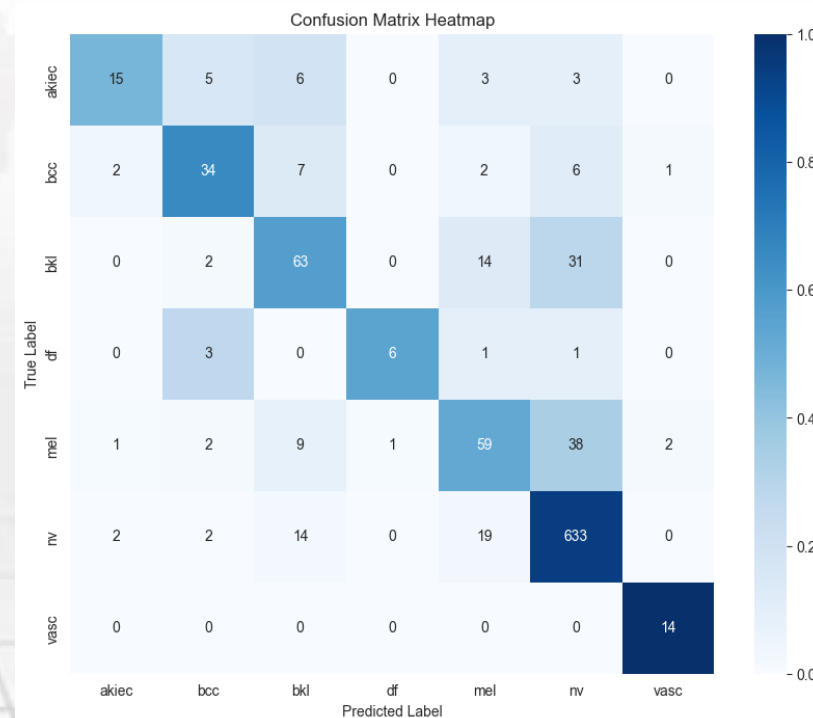
# Implementation & Results

The best model of after adjust hyperparameter:  
Accuracy is up to 82%:



Classification Report:

	precision	recall	f1-score	support
akiec	0.75	0.47	0.58	32
bcc	0.71	0.65	0.68	52
bkl	0.64	0.57	0.60	110
df	0.86	0.55	0.67	11
mel	0.60	0.53	0.56	112
nv	0.89	0.94	0.92	670
vasc	0.82	1.00	0.90	14
accuracy			0.82	1001
macro avg	0.75	0.67	0.70	1001
weighted avg	0.81	0.82	0.82	1001





# Implementation & Results

GUI web:

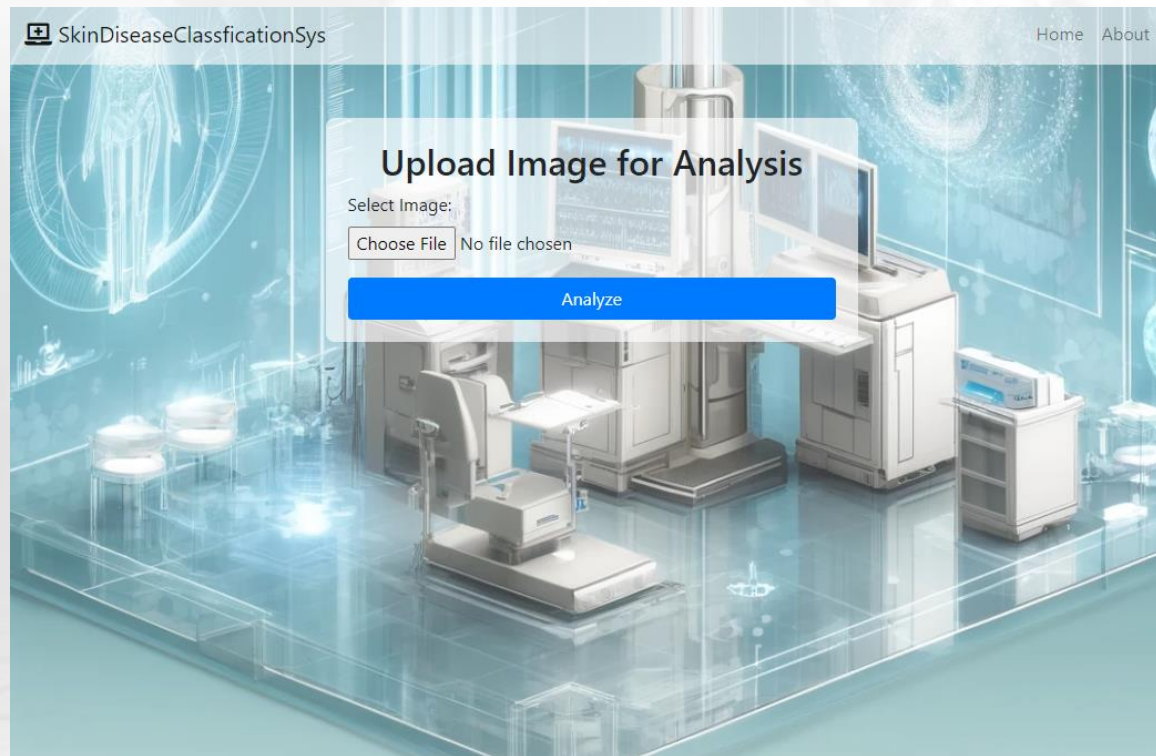
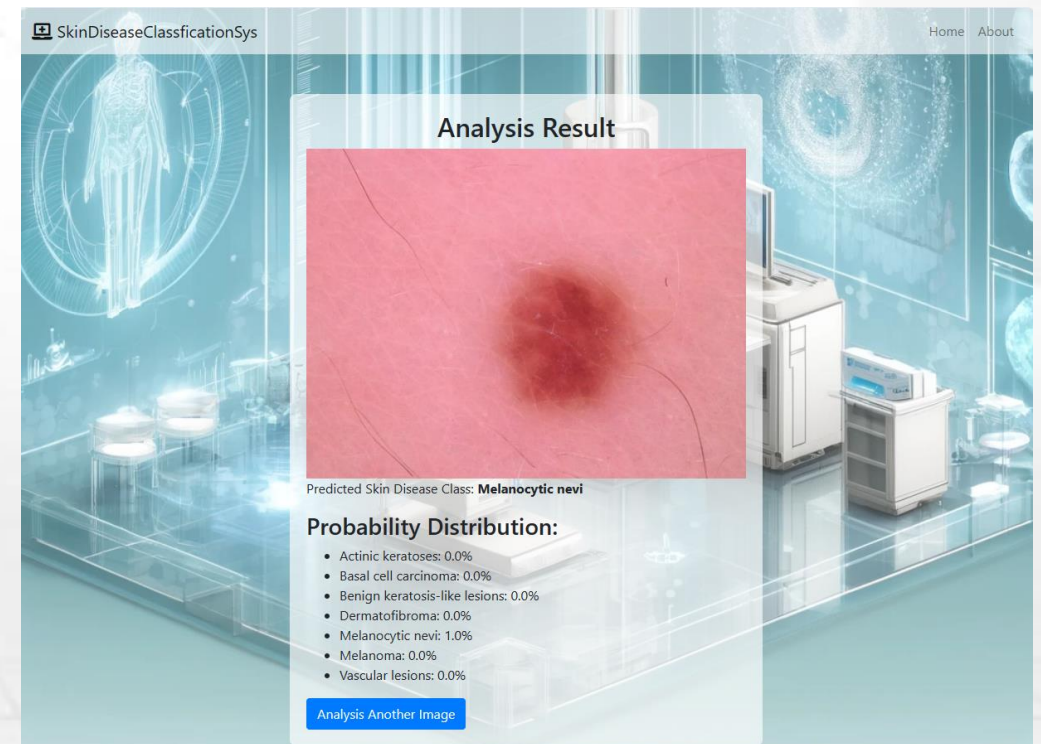


Image upload page



Result page

Use flask to make the model in the backend interact with the frontend



# Conclusion

Achievement ,Limitation, Future work

## Achievement

This project successfully fusion depthwise separable convolutions in the Inception model, improved the classfication of skin disease. The depthwise separable model finally get 82% accuracy.

# Limitation

- Limitation of dataset
- Overfitting risk
- Limitation of generalization

## Future work

- Extend dataset
- Combine multimodal data
- Using the latest deep learning techniques

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# Thanks for listening

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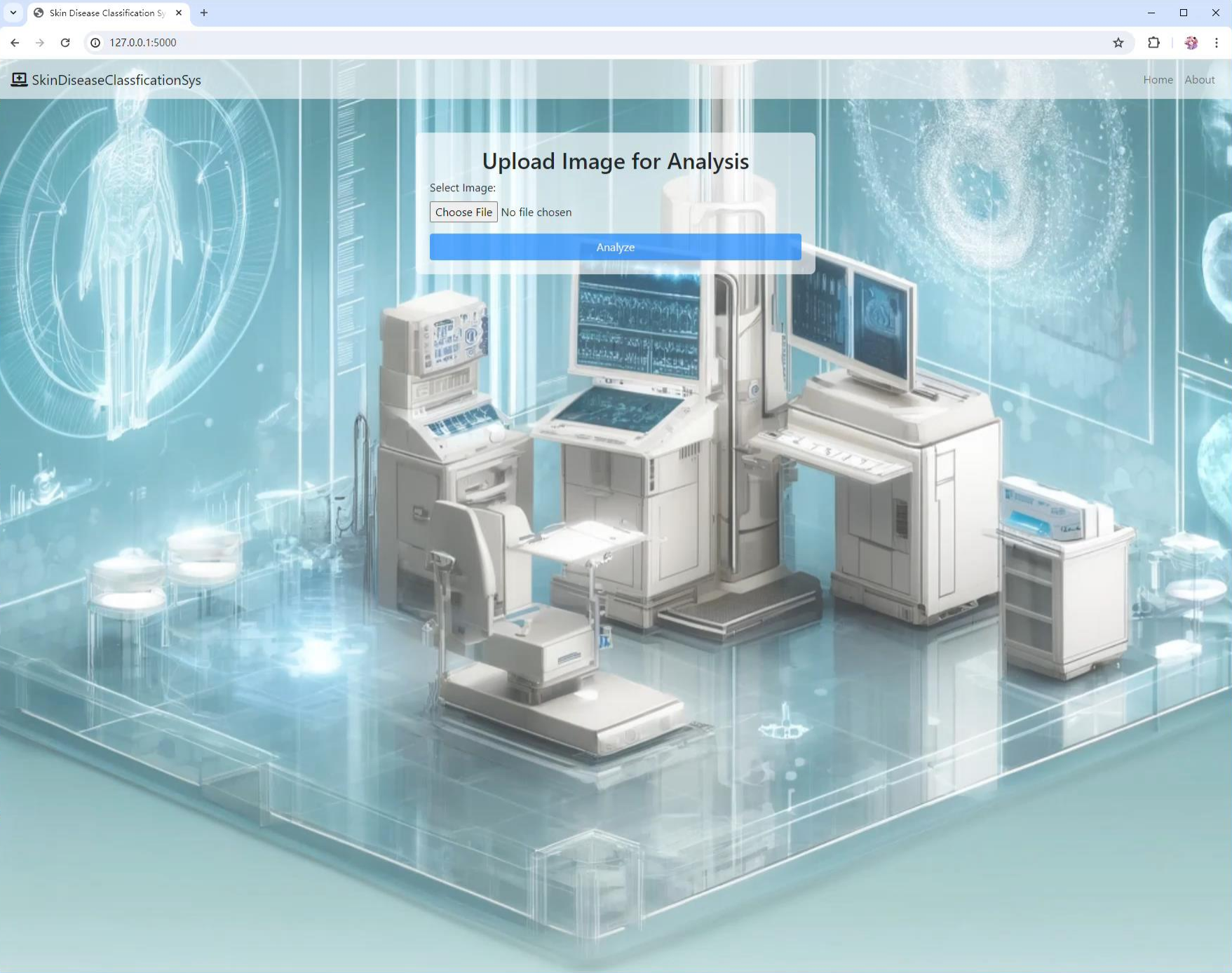
## Reference

- [1] “Key Statistics for Melanoma.” [Online]. Available: <https://www.cancer.org/cancer/types/melanoma-skin-cancer/about/key-statistics.html>
- [2] P. Tschandl, C. Rosendahl, and H. Kittler, ‘The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions’, *Sci Data*, vol. 5, no. 1, p. 180161, Aug. 2018, doi: 10.1038/sdata.2018.161.
- [3] C. Szegedy *et al.*, ‘Going deeper with convolutions’, in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Boston, MA, USA: IEEE, Jun. 2015, pp. 1–9. doi: 10.1109/CVPR.2015.7298594.
- [4] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi, ‘Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning’, *AAAI*, vol. 31, no. 1, Feb. 2017, doi: 10.1609/aaai.v31i1.11231.
- [5] A. G. Howard *et al.*, ‘MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications’. arXiv, Apr. 16, 2017. Accessed: Oct. 27, 2023. [Online]. Available: <http://arxiv.org/abs/1704.04861>

A faint, light gray world map is visible in the background, centered behind the text.

**Demo**





A faint, light gray world map is visible in the background, centered behind the text.

# Q&A

A horizontal line with a dashed segment on the left and a solid segment on the right, featuring a small diamond shape at the junction.A perspective grid of thin gray lines covers the bottom half of the image, creating a sense of depth and space.