Lab3: Image classification

3099704 AI for Digital Health (2025/2)

Objective

- **Create and train** image classification models with Teachable Machine and the PyTorch library.
- **Tune hyperparameters** of image classification models.
- **Inference & evaluate** performance each model

Material

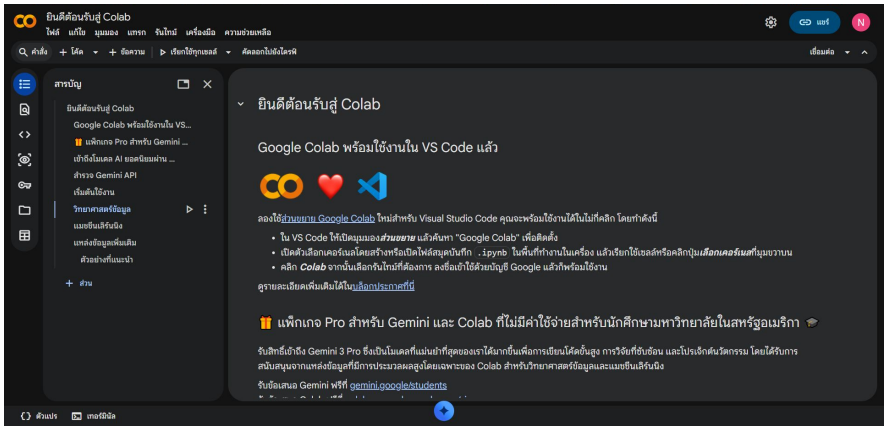
- **Google Colab** is a free cloud-based platform that run jupyter notebook (Python code) in a browser, without needing local setup.

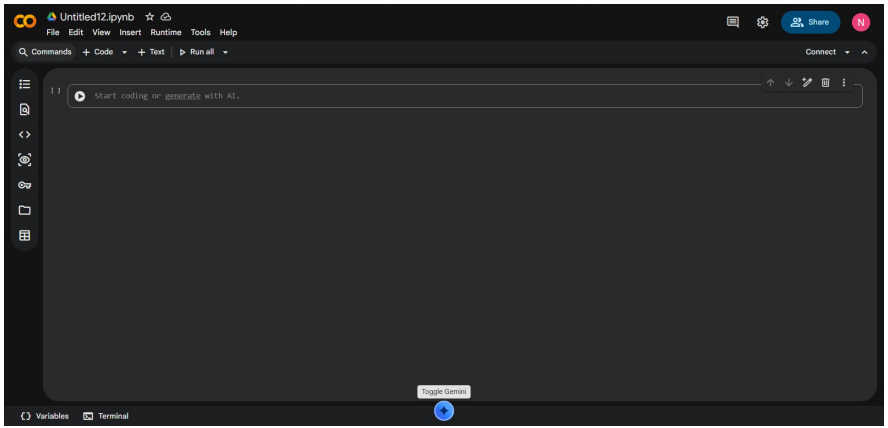
- **Teachable Machine** is a web-based tool by Google that trains machine learning models for images, audio, or poses without coding.

- **PyTorch, TenserFlow** is an deep learning library that enables building, training, and deploying neural networks using Python

Material

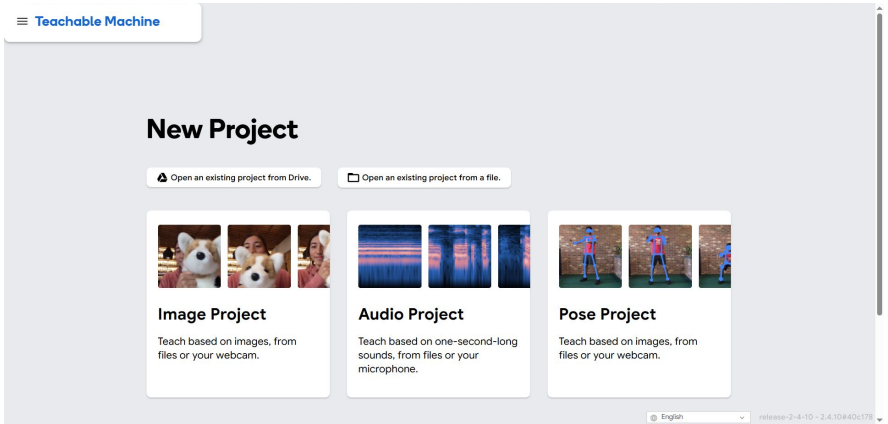
- With **Google Colab**, you don't need to install any software. All you need is a Google account, and you can start using it right away. Simply visit: https://colab.research.google.com/ or select NEW NOTEBOOK to start a new file.

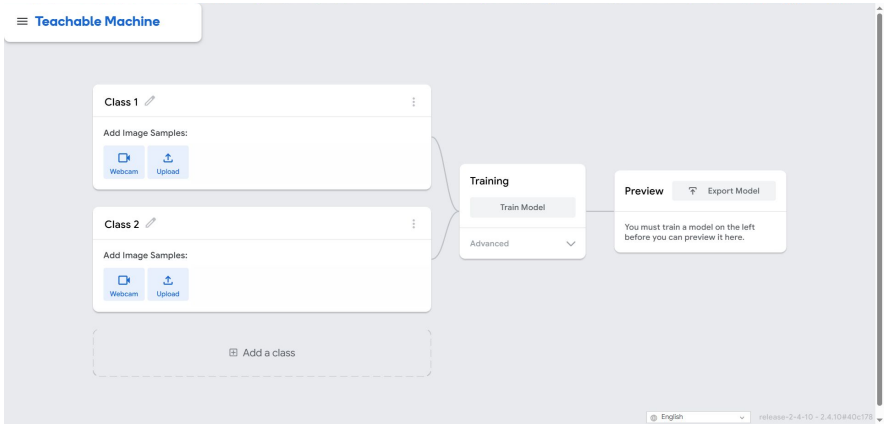




Material

- **Teachable Machine** is a web-based tool from Google that allows you to easily create models without writing code or installing software. Simply access it through your web browser at https://teachablemachine.withgoogle.com/



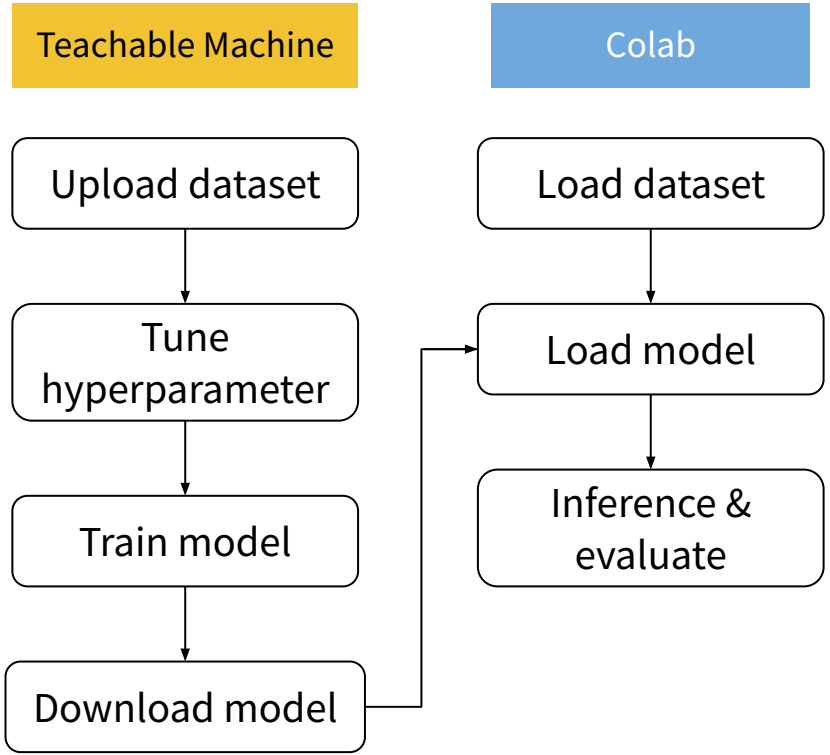


Material

- **TensorFlow and PyTorch** are deep learning libraries used with Python. They can be run either on a local computer or on Google Colab, and can be installed easily using the **pip install** command.

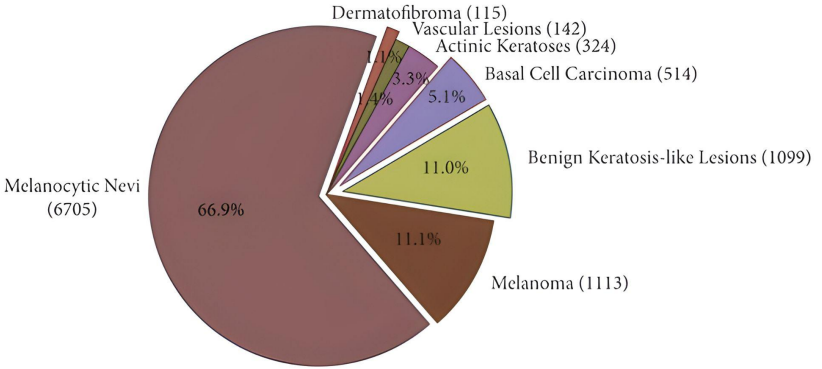
Lab3.1: MobileNet (Teachable Machine)

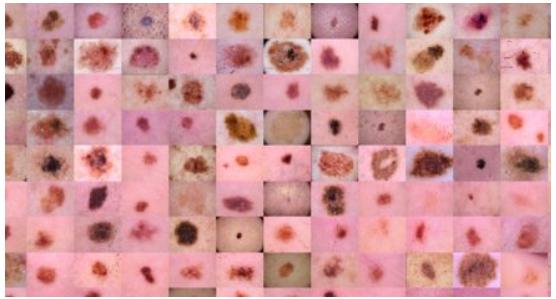
In this lab, you will create an image classification model using **Teachable Machine** and then evaluate its performance using a **Google Colab notebook.**



Dataset: Skin Cancer MNIST: HAM10000

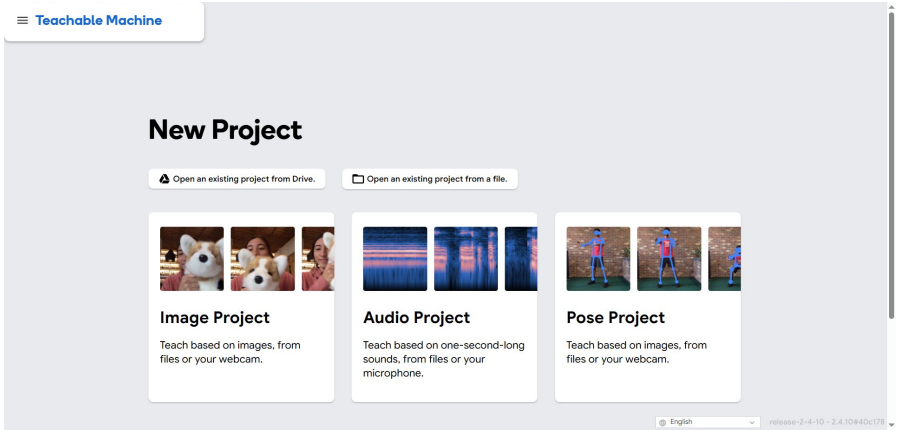
- The dataset consists of 10015 images with 10013 labeled objects belonging to 7 skin cancer classes.
- The data contains image in JPG format and documents in JSON format
- In the experiment, we reduced the amount of data and formatted it to simplify the experiment.

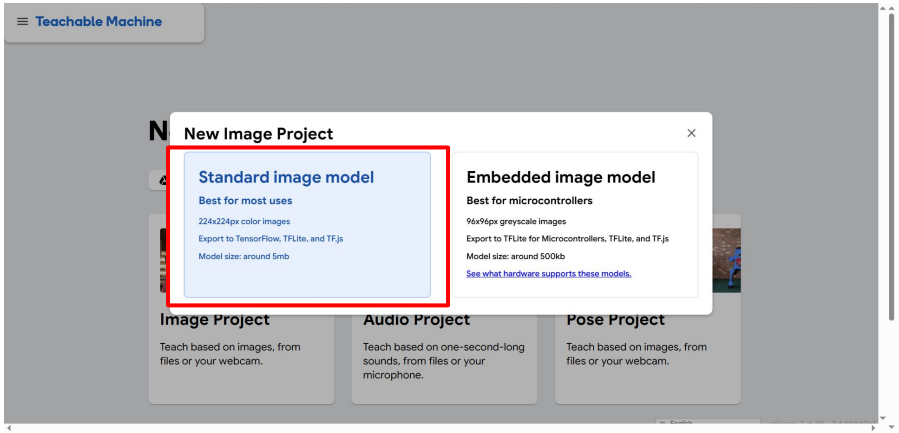




Lab3.1: MobileNet (Teachable Machine)

1) Create image project(standard image model) in Teachable Machine





Lab3.1: MobileNet (Teachable Machine)

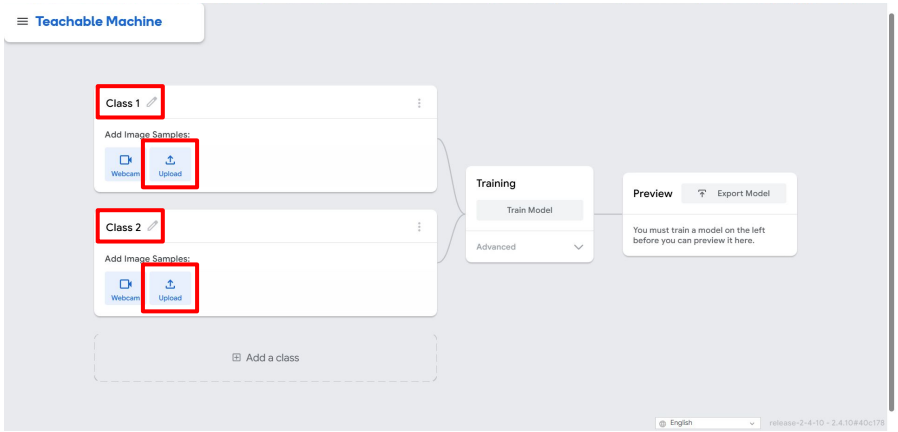
2) Download the dataset from GitHub, then upload the image samples and set labels in **Teachable Machine**.

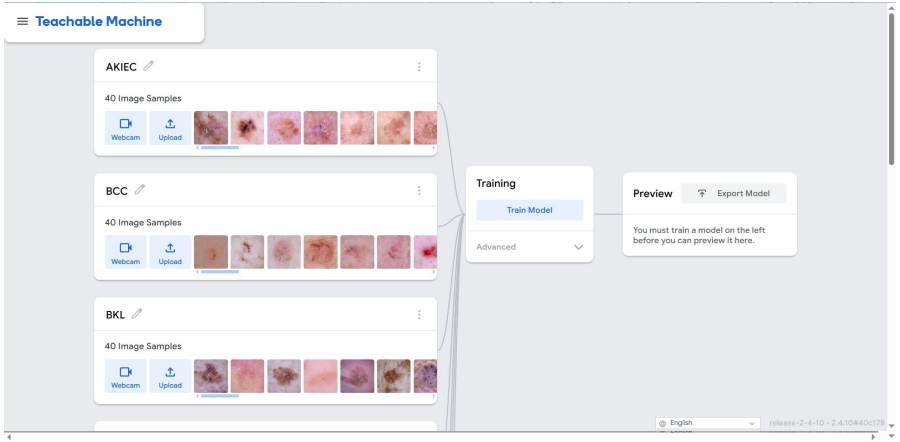
HAM10000_TM directory

```
HAM10000_TM
├── train/
    ├── AKIEC/
    .    ├── ISIC_0024329.jpg (original image)
    .    .
    .    .
    └── VASC/
        ├ . . .
```

Lab3.1: MobileNet (Teachable Machine)

2) Download the dataset from GitHub, then upload the image samples and set labels in Teachable Machine.

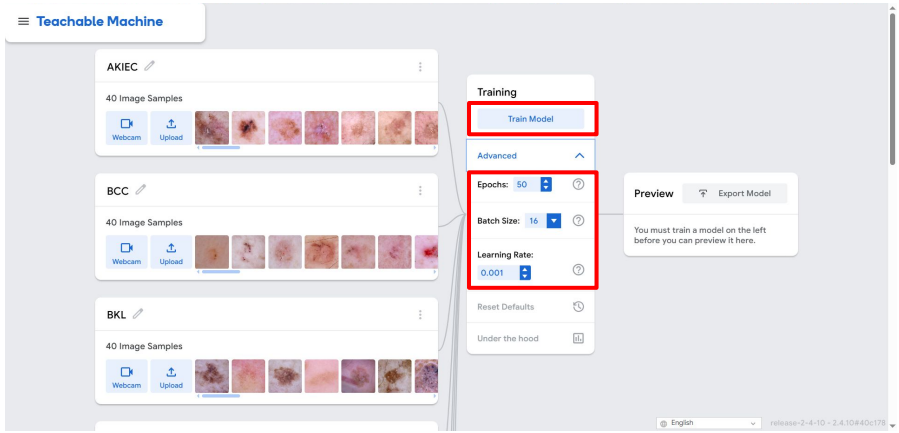




Lab3.1: MobileNet (Teachable Machine)

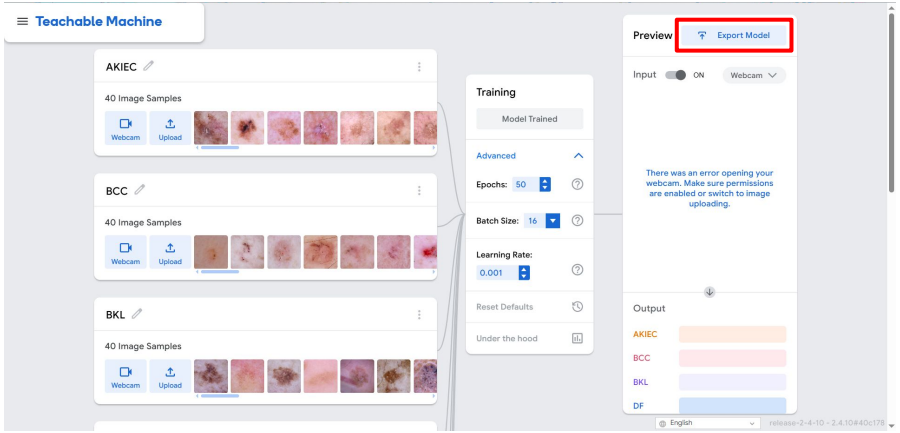
3) Tune learning parameter & Train model

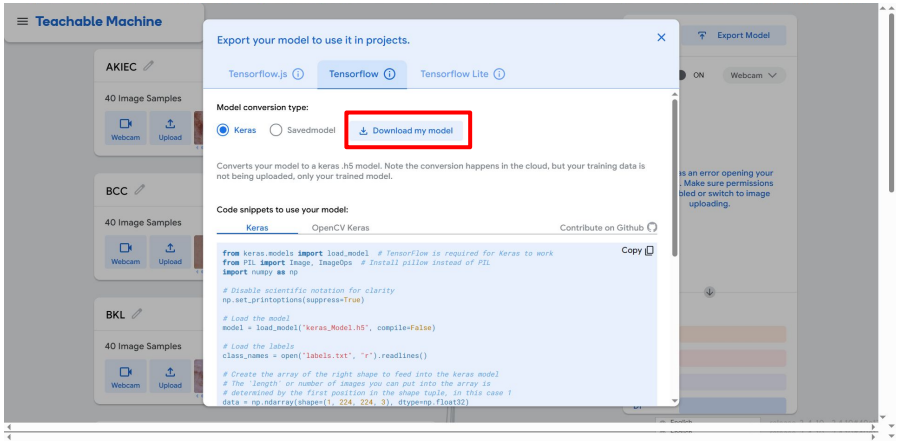
   a) epoch: [5, 20, 50, 100]
   b) learning rate: [0.00001, 0.001, 0.1]



Lab3.1: MobileNet (Teachable Machine)

4) Export model (tensorflow version)

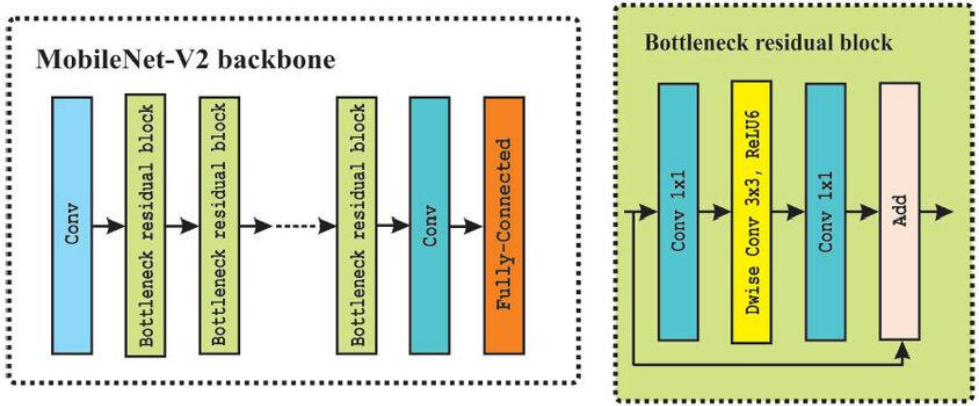




Lab3.1: MobileNet (Teachable Machine)

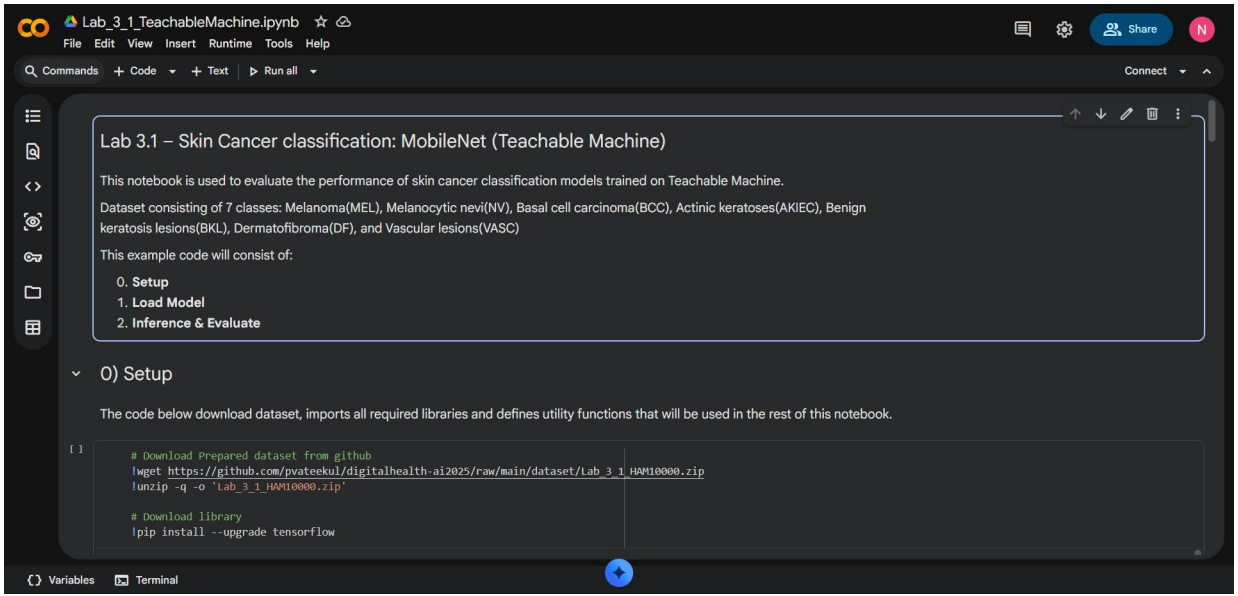
The image model in Teachable Machine is MobileNet V2, with the following details:

- There are 3 layers for bottleneck block.
- This time, the **first layer** is **1×1 convolution with ReLU6.**
- The **second layer** is the **depthwise convolution**.
- The **third layer** is another **1×1 convolution but without any non-linearity.**



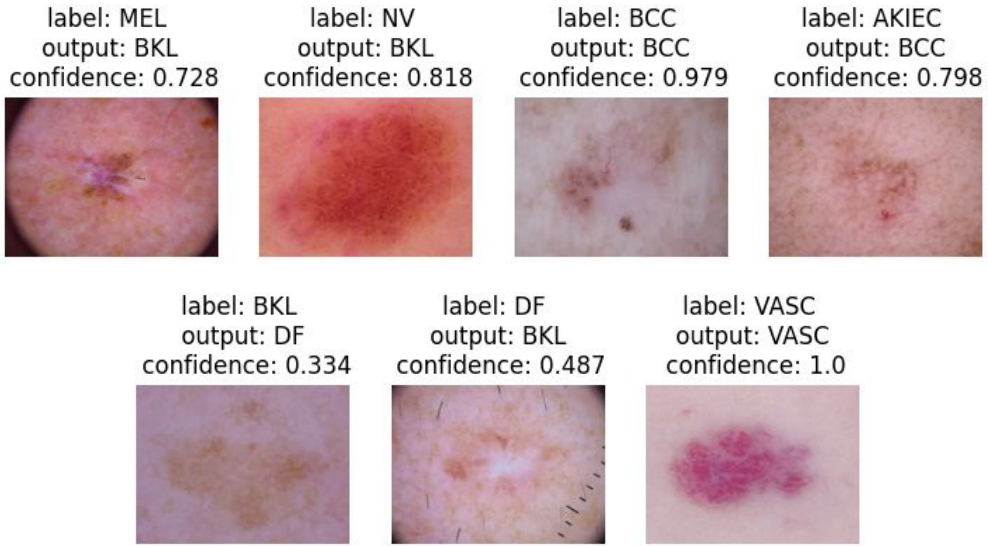
Lab3.1: MobileNet (Teachable Machine)

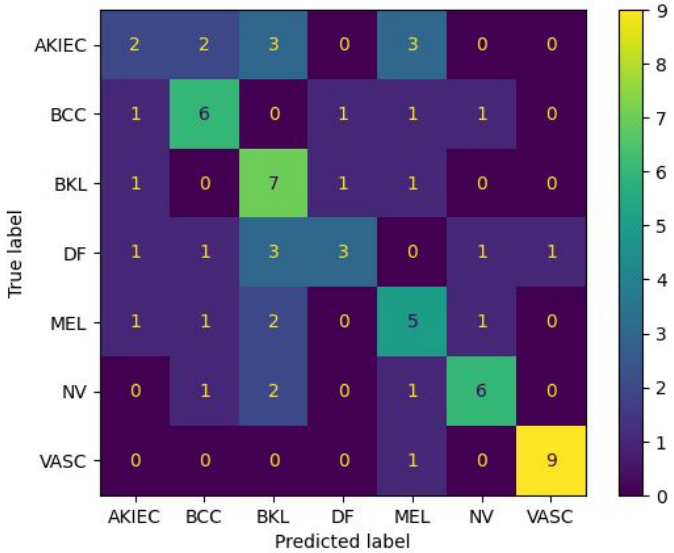
5) Open Lab_3_1_TeachableMachine.ipynb (in **colab**)



Lab3.1: MobileNet (Teachable Machine)

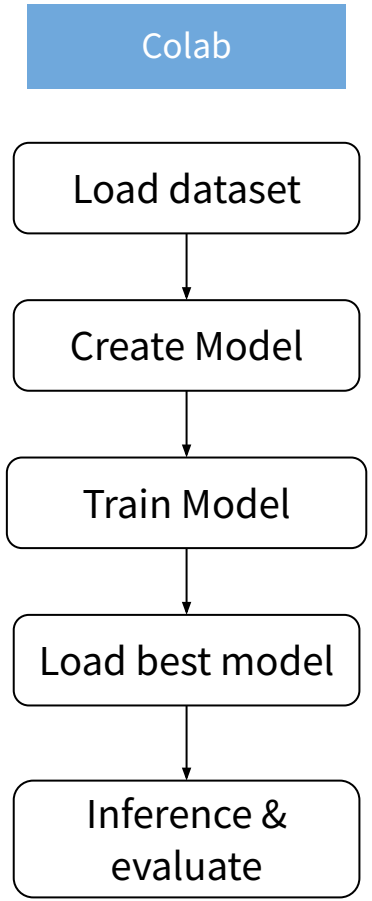
6) Run Lab_3_1_TeachableMachine.ipynb for evaluation & inference.





Lab3.2: EfficientNet (Pytorch)

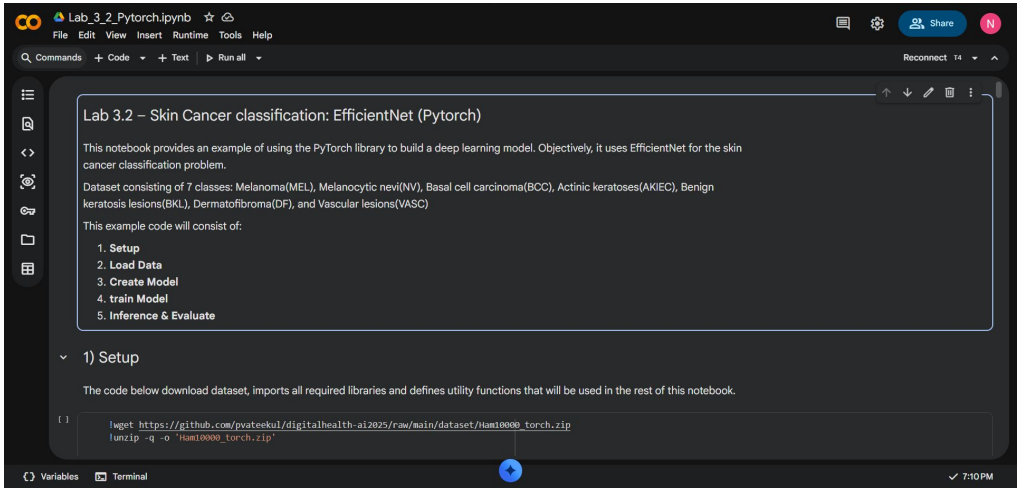
In this lab, you will create an image classification model and then evaluate its performance using **Pytorch library**



Lab3.2: EfficientNet (Pytorch)

Run Lab_3_2_PyTorch.ipynb (in colab)

1) Setup
2) Load Data
3) Create Model
4) train Model
5) Inference & Evaluate



Lab3.2: EfficientNet (Pytorch)

In this lab, we chose to use EfficientNet V2, which has the following key architectural innovations:

- **Fused-MBConv Blocks:** Replace standard MBConv with a fused 3×3 conv for faster computation without adding many parameters.
- **Smaller Kernels and Expansion Ratios:** The architecture favors smaller 3x3 kernel sizes and smaller expansion ratios within the MBConv blocks, which reduces memory access overhead.
- **Removal of the Final Stage:** The final stride-1 stage of the original EfficientNet is removed to further lower parameter count and memory consumption.