Teachable machine

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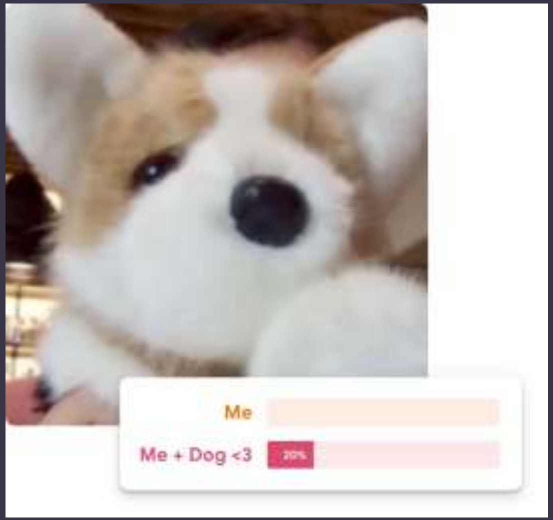


Roadmap

AI, ML, DL?

How have AI evolved?

Teachable machine

- Intro
- Collect data
- Train models
- Infer from image
- Export model

Prospects

- Applications

Background of AI

Back in 1958, Frank Rosenblatt at Cornell design the first artificial neural network

- Described presciently as “**Pattern-recognizing device**”
- Era of mainframe computers filled rooms and ran on vacuum tubes
- Inspired by the interconnections between neurons in the brain

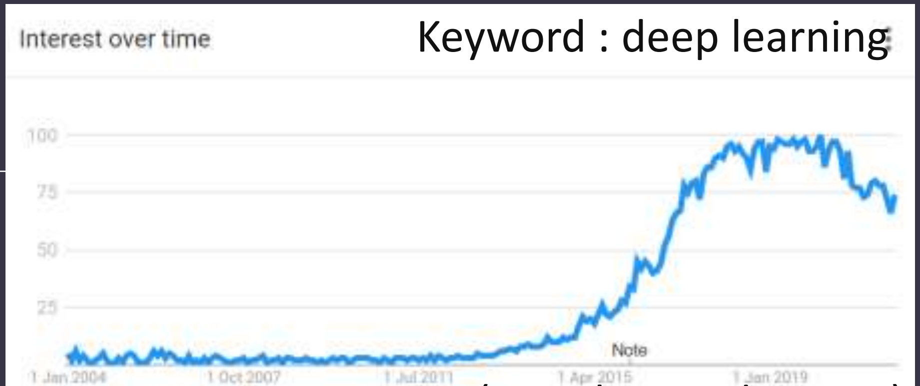
Limitation of computing hardware soon overcame

- **Moore's Law** and other improvements in hardware
- Yielded a roughly 10-million-fold increase in the number of computations that a computer could do in a second
- Inclusion GPU in computation

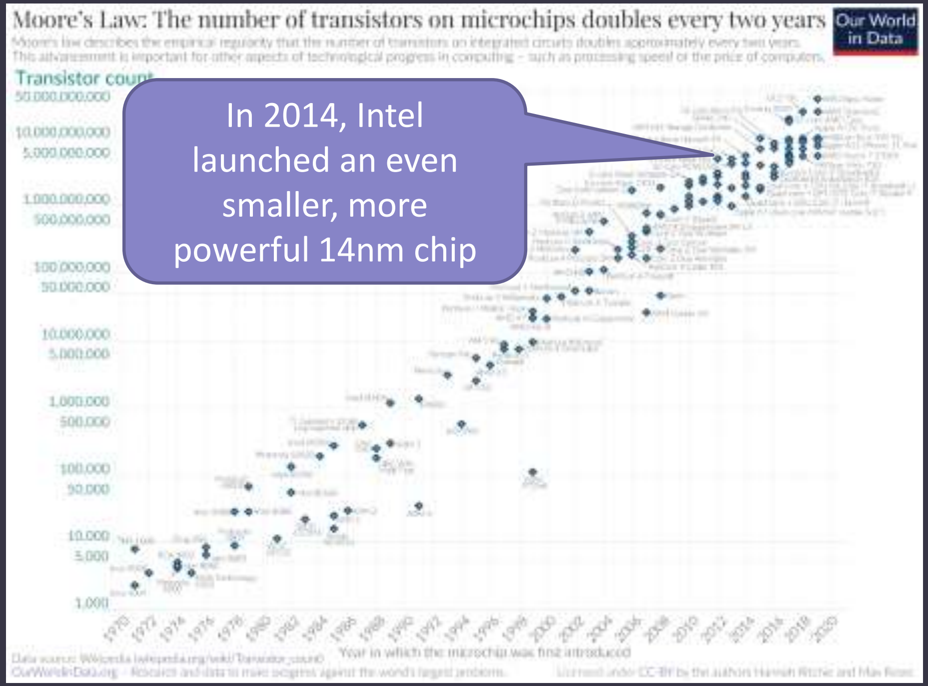
Interest in artificial intelligence (AI) is revisited in the late 2000s

- Tools available up to the computing challenge
- Renamed as “**deep learning**"
- Extra layers of neurons is introduced

Observation that the transistors amount in a dense integrated circuit (IC) doubles about every two years

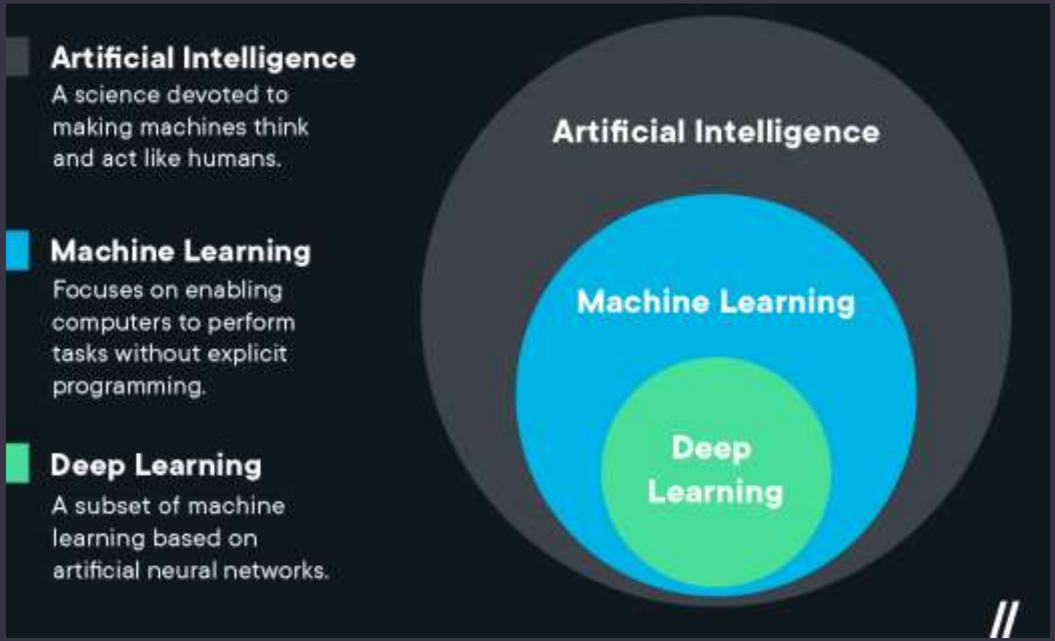


(Google Trends, 2021)

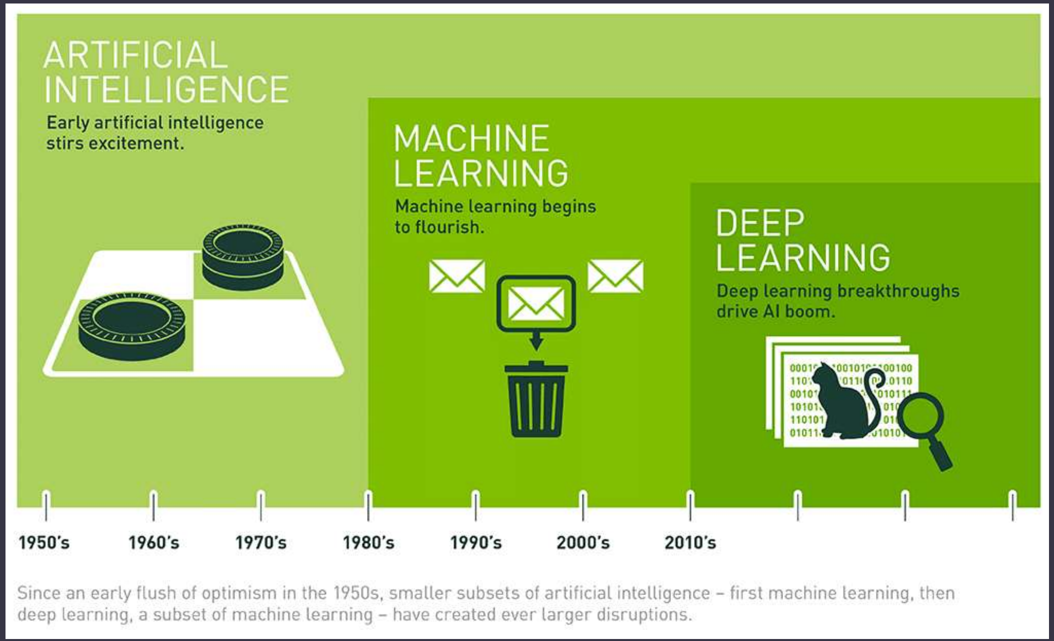


(Thompson et al., 2021)

AI, ML, DL?



(Middleton, 2021)



(Copeland, 2016)

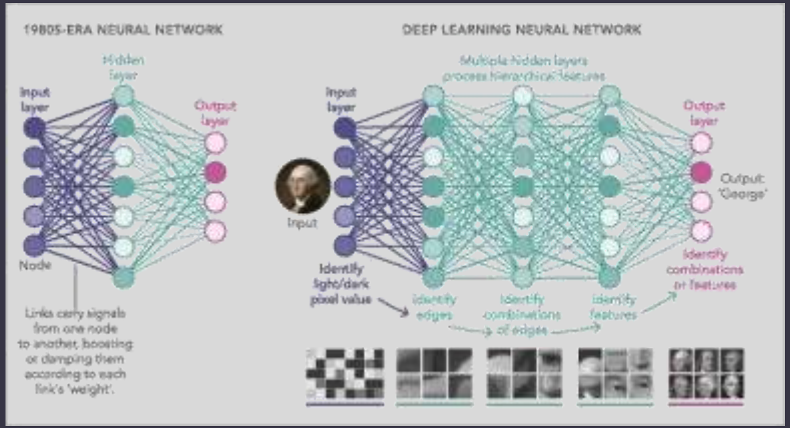
ML / DL

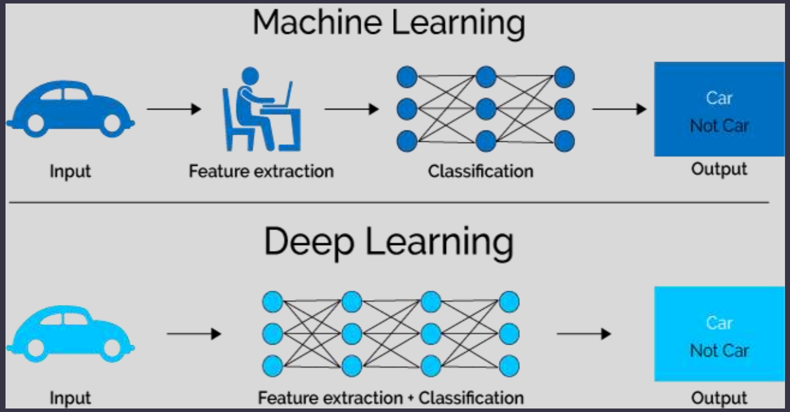
Expert-knowledge based model (ML)

- Modelling based on professional know-how
- (Geotechnical) modelling with governing equations
- Early AI were rule based, applying logic and expert knowledge to derive results (machine learning)
  - Supervised / semi-supervised / unsupervised
  - Reinforcement learning

Flexible statistical models (most AI/DL)

- Require myriad combinations of priori, activation functions, bias, weighting and networks
- Use numerous neurons (in **neural networks**) to train suitable AI model
- Provide outcomes with probability [87% cat]





(Mahapatra, 2019)

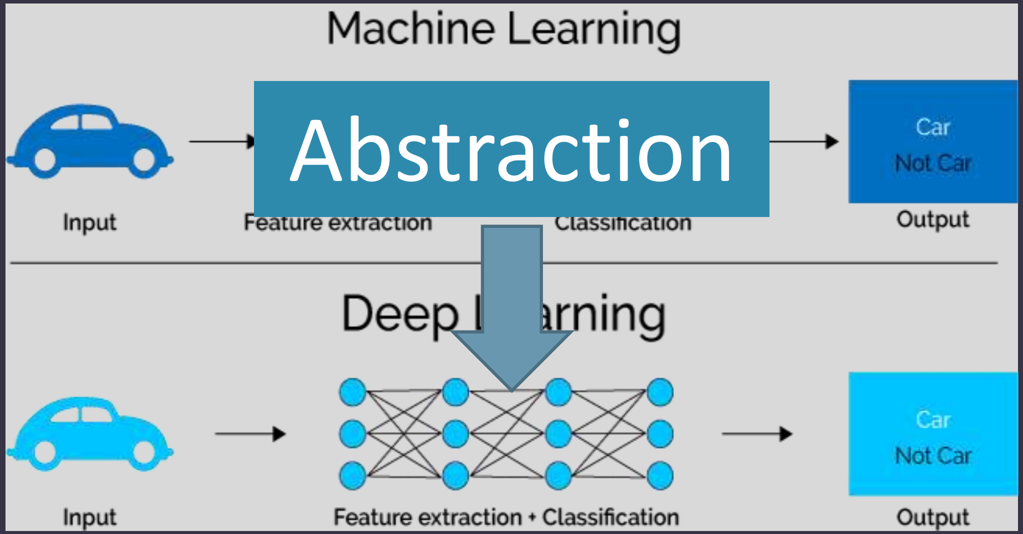
From ML to DL

Machine learning

- Computers still think and act like machines
- Needs **manual** feature extraction

Deep learning

- Computers learn to think using structures modeled from human brain
- Multi-layered “deep neural networks”
- Non-linear data transformation => increasingly abstract



ML vs DL

	Machine learning	Deep learning (NN)
Hardware	Less complex Run on conventional computers	Powerful hardware GPU for parallel computing
Time	Quick set up and operation Limited in performance	More setup time Instantaneous result, improved quality over time with more data
Approach	Structured data Traditional algorithms (e.g. linear regression)	large volumes of unstructured data Neural networks
Applications	Already in use in your email inbox, bank, and doctor's office	Complex and autonomous programs (e.g. self-driving cars / robots that perform advanced surgery)

(Middleton, 2021)

Deep learning

Feedforward neural network

- Simplest neural network
- Maybe with single/multi-layer neurons + backpropagation (multi-layer perceptron)
- Input layer => hidden layer => output layer

Convolutional Neural Networks (CNN)

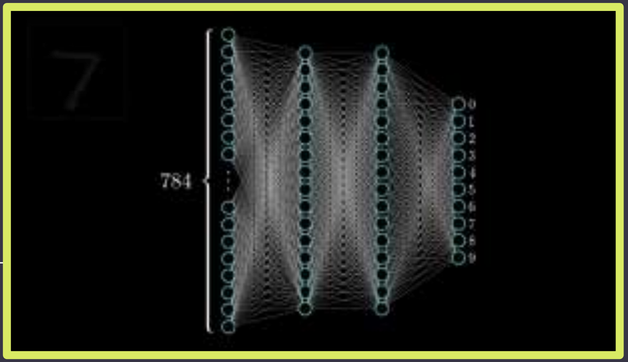
- Convolution : process of applying weight-based filter across every element of an image
  - Assist in computer vision, helping computer to “see” and “understand” what is in the picture
- Designed to work with images
- Good for feature scanning in image
  - Identify people, cars, shipwreck at ocean floor, landslide
- Highest growth over the decade

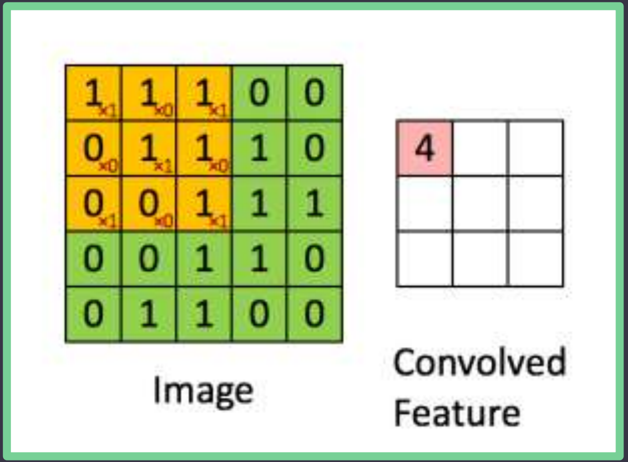
Recurrent Neural Networks (RNN)

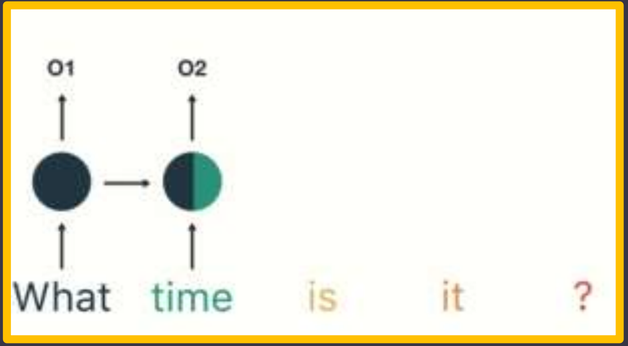
- Introduce **MEMORY** in algorithm
  - Computer remembers past data and decisions, include in consideration of current data
- Natural language processing : considers tone and content in text comprehension
  - Personality chat robot : **NLP** (Natural language processing) **+** LSTM (Long Short-term Memory)
  - Personal assistance (Hey Siri , OK Google…)
- Map direction : remembers best route by majority of people

More to come…

- Combinations of multiple RNN/CNN

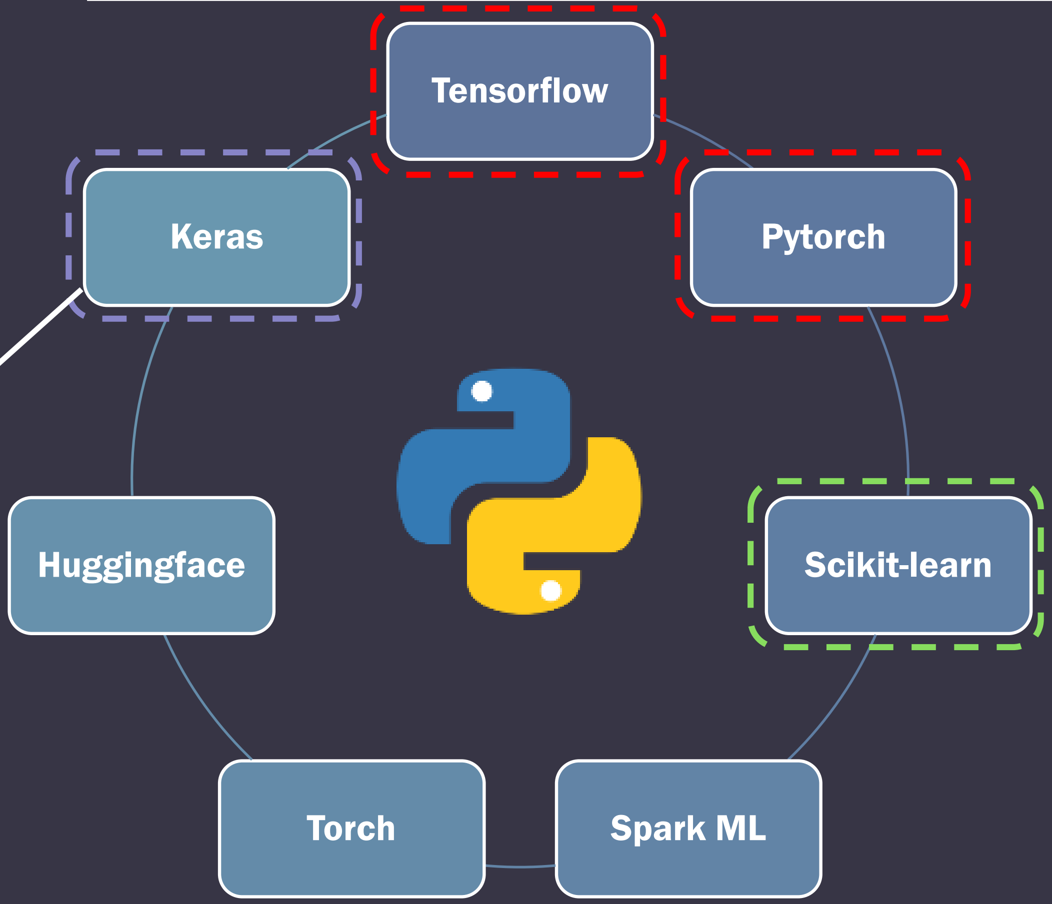






(Phi, 2018)

Main ML/DL frameworks



Neural network library built on top of **TensorFlow**

Machine learning relies on algorithms

- ML/DL frameworks simplify this process
- tool, interface, or library for easy development of AI model
- without understanding the underlying algorithms

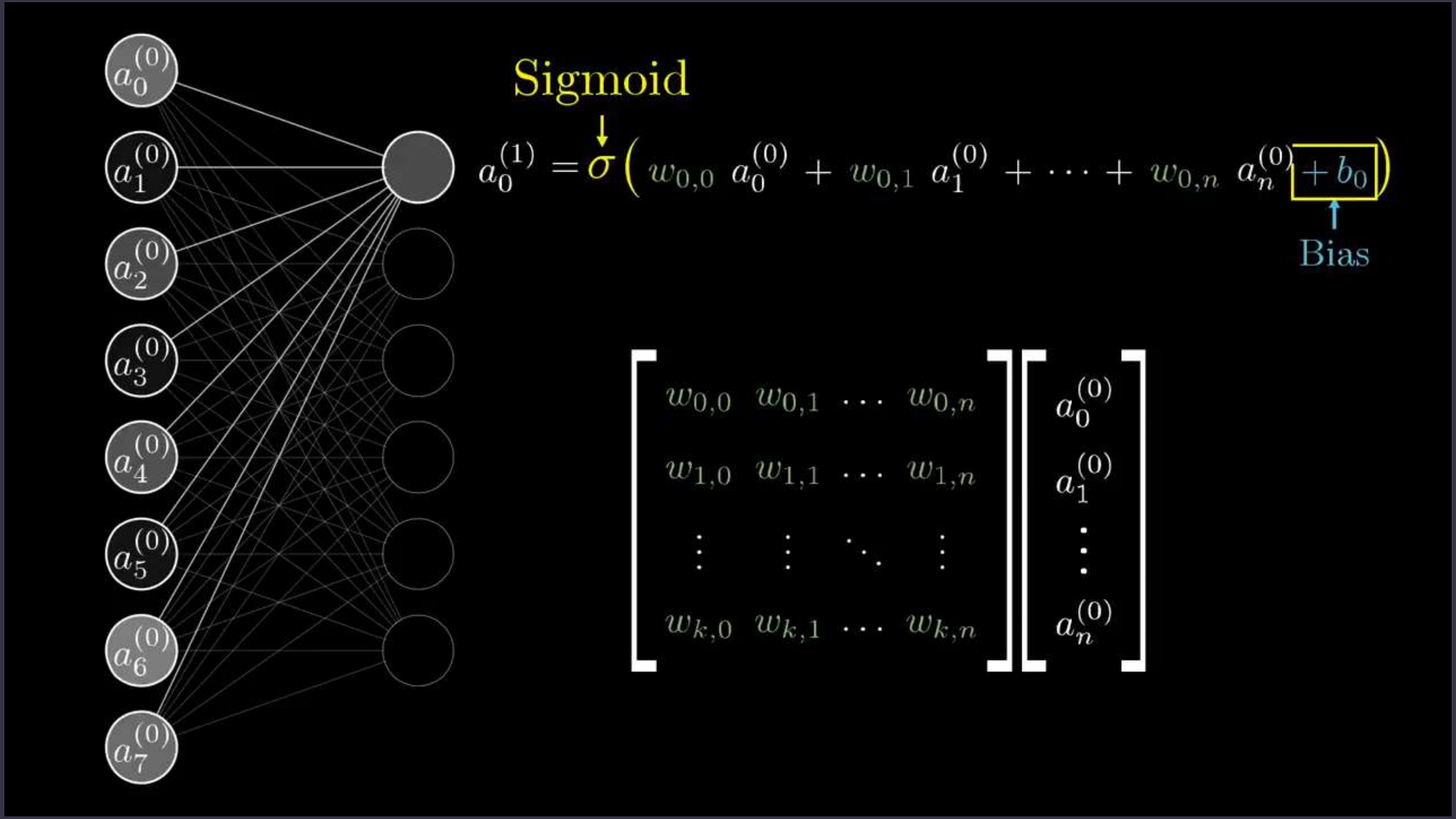
Python is the predominant ML programming language

- Do we use Tensorflow or Pytorch?
  - Tensorflow : Google Brain
  - Pytorch : Facebook AI Research (FAIR)
  - scikit-Learn : Old standards of the data science world, great ML tool for quick interpretation
- All are interchangeable

Don't reinvent the wheel

- Unless you want to change <u>fundamentally</u>

But what is a neural network?



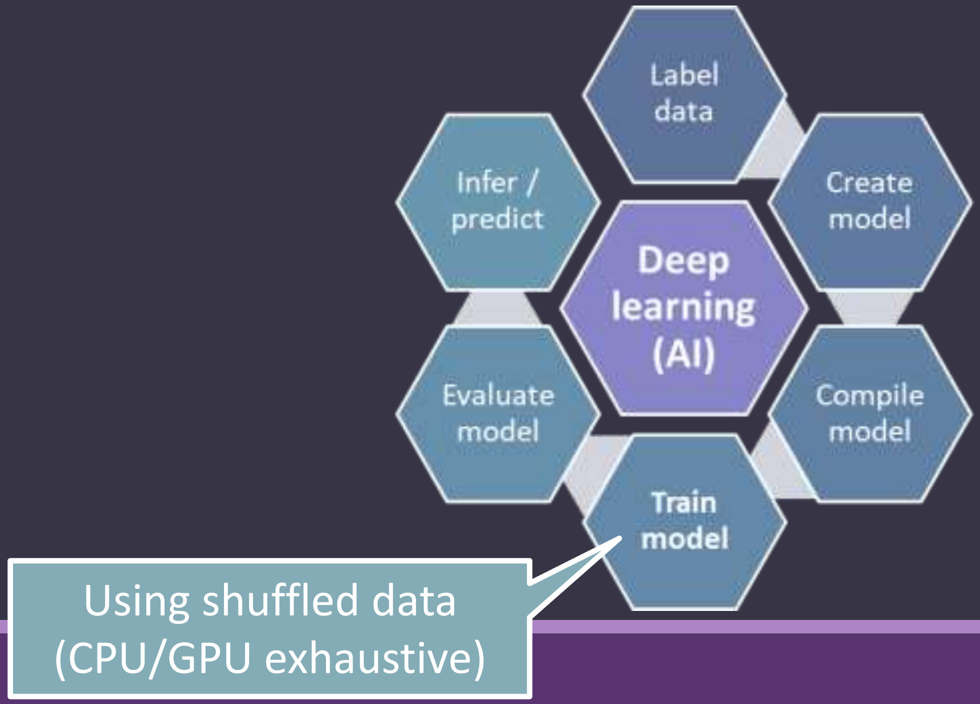
(3blue1brown, 2017)

AI too complicated?

- START SIMPLE

Teachable machine

- GOOGLE INC.
- BRIDGE FROM ML TO DL
- TEACH MACHINES TO THINK (DL)

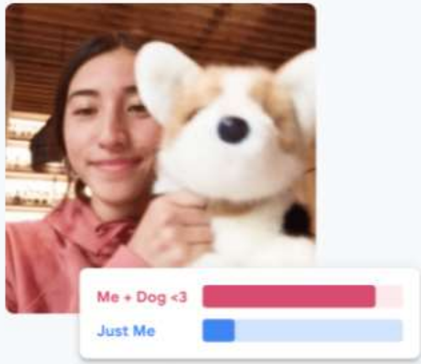


Gather | Train | Infer

Teachable Machine — About — FAQ — Get Started

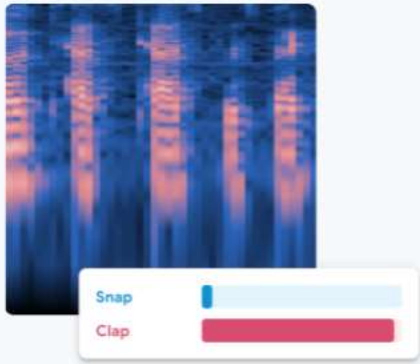
What can I use to teach it?

Teachable Machine is flexible – use files or capture examples live. It's respectful of the way you work. You can even choose to use it entirely on-device, without any webcam or microphone data leaving your computer.



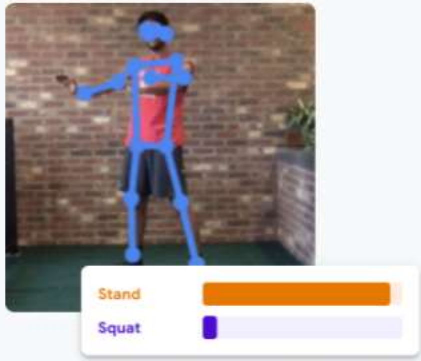
Images

Teach a model to classify images using files or your webcam.



Sounds

Teach a model to classify audio by recording short sound samples.

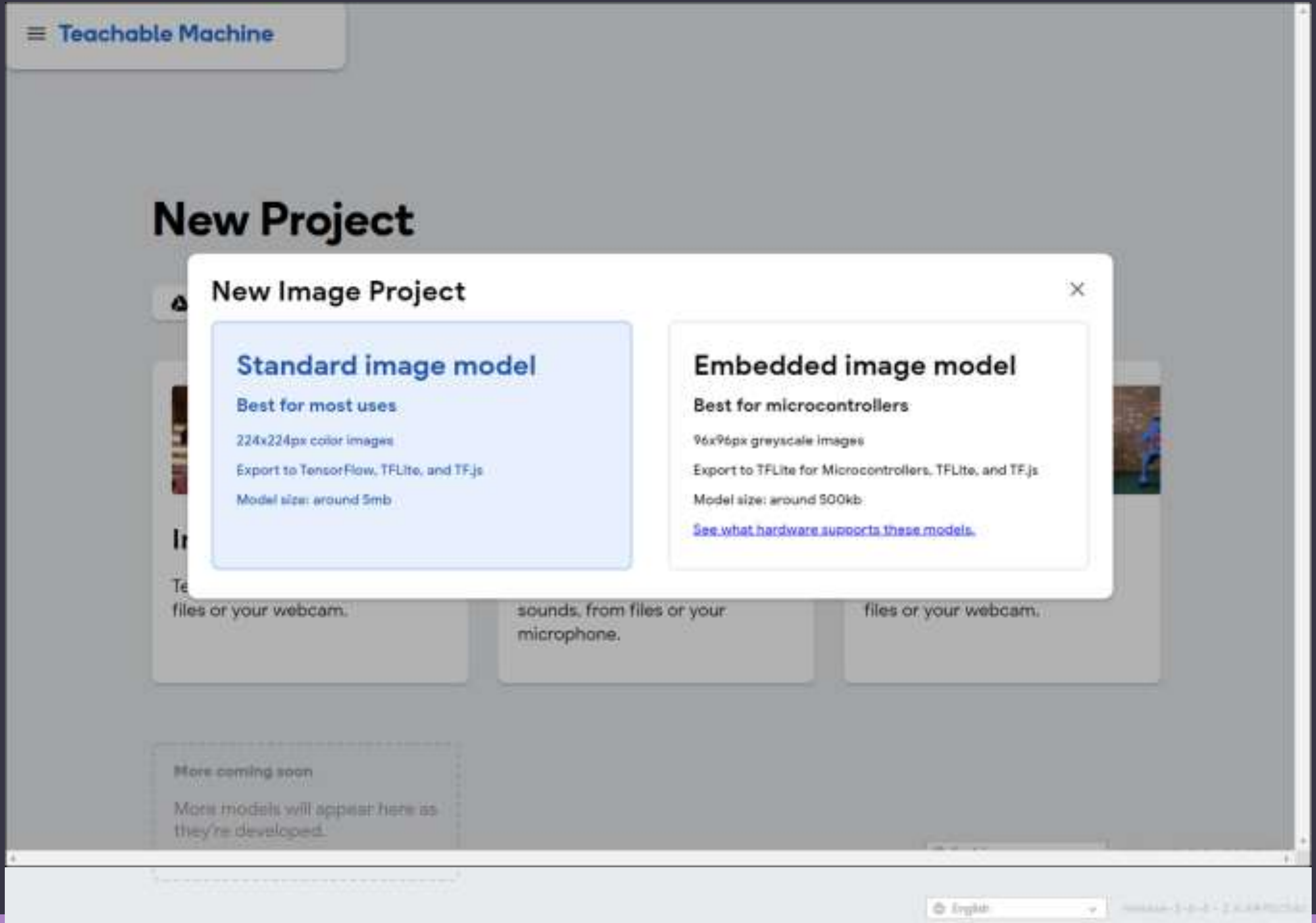


Poses

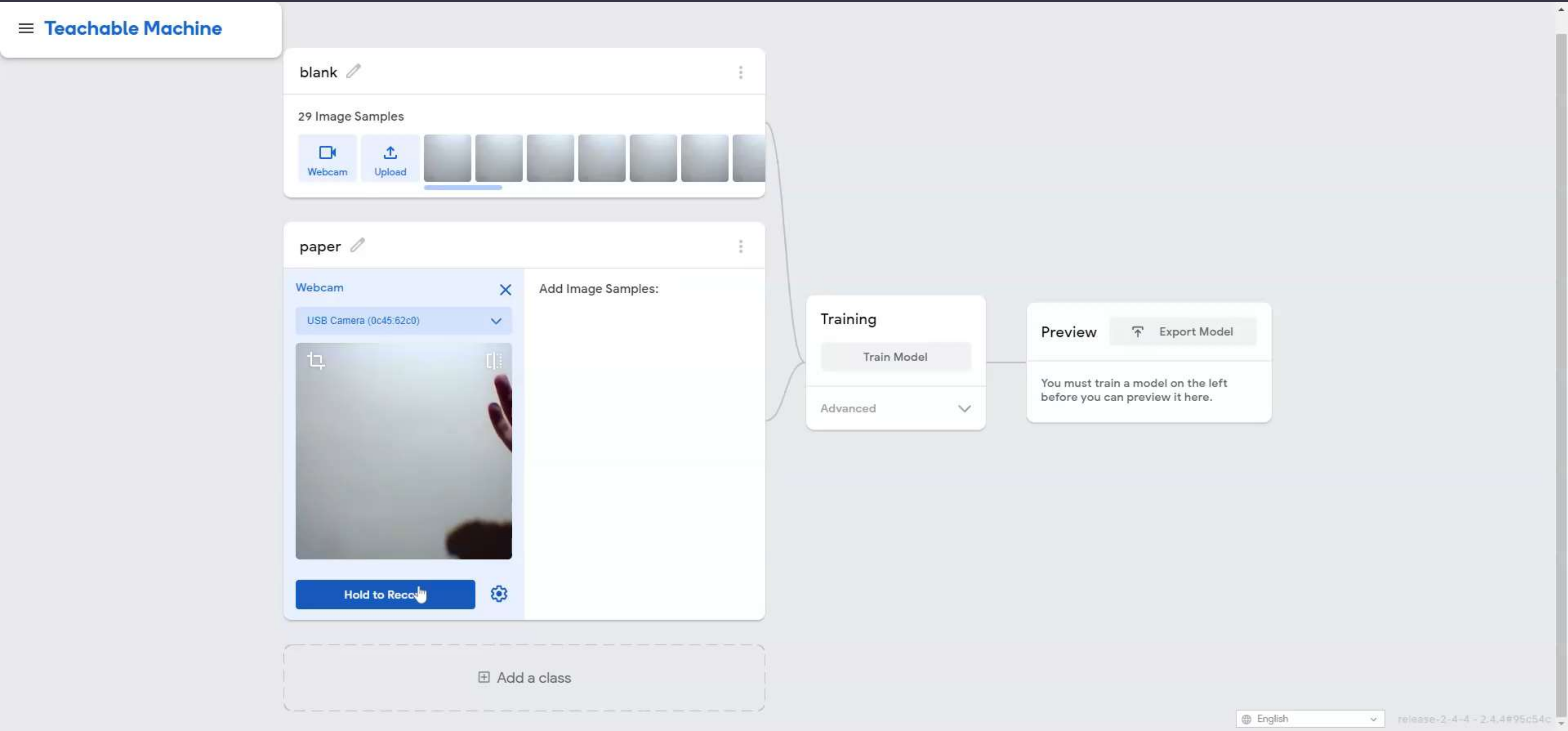
Teach a model to classify body positions using files or striking poses in your webcam.

Gather | Train | Infer

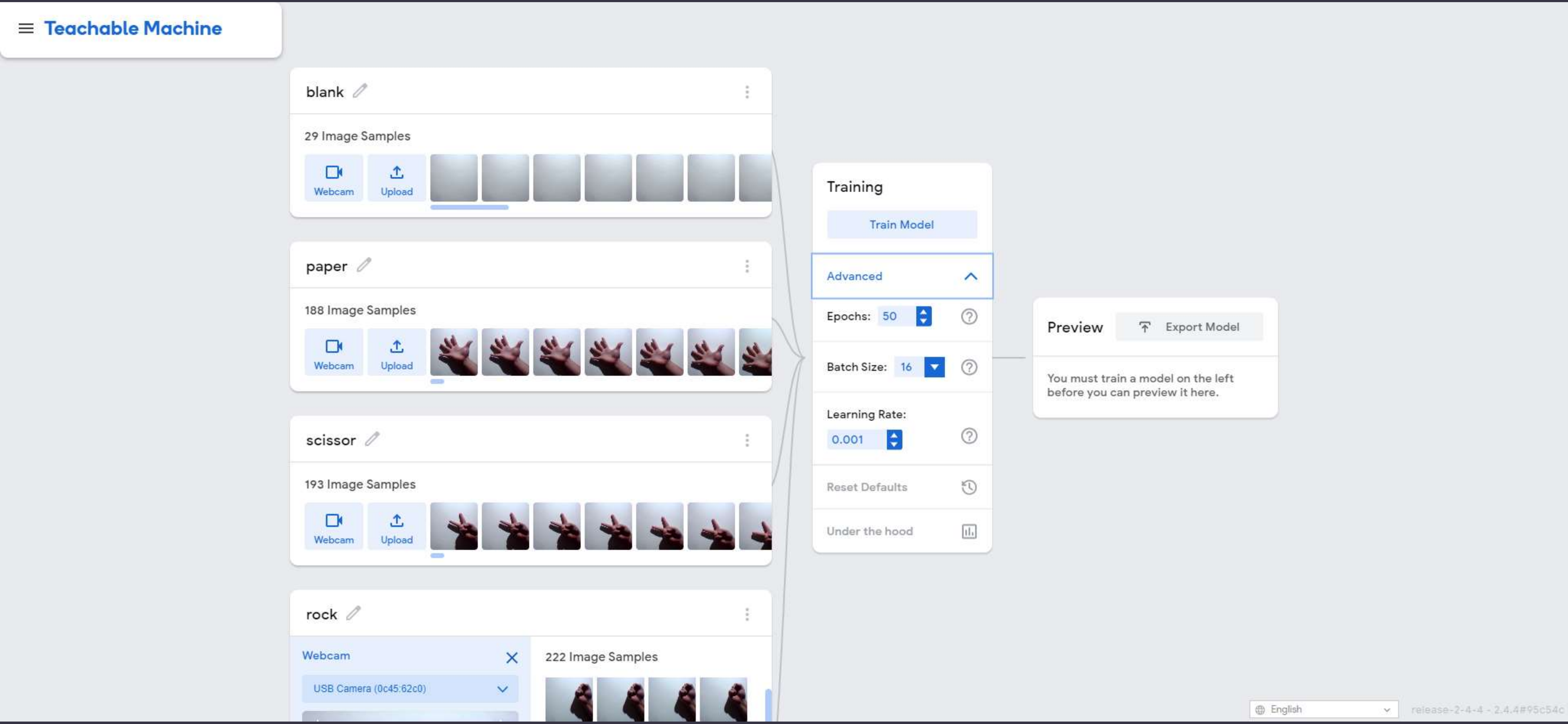
Create a new project



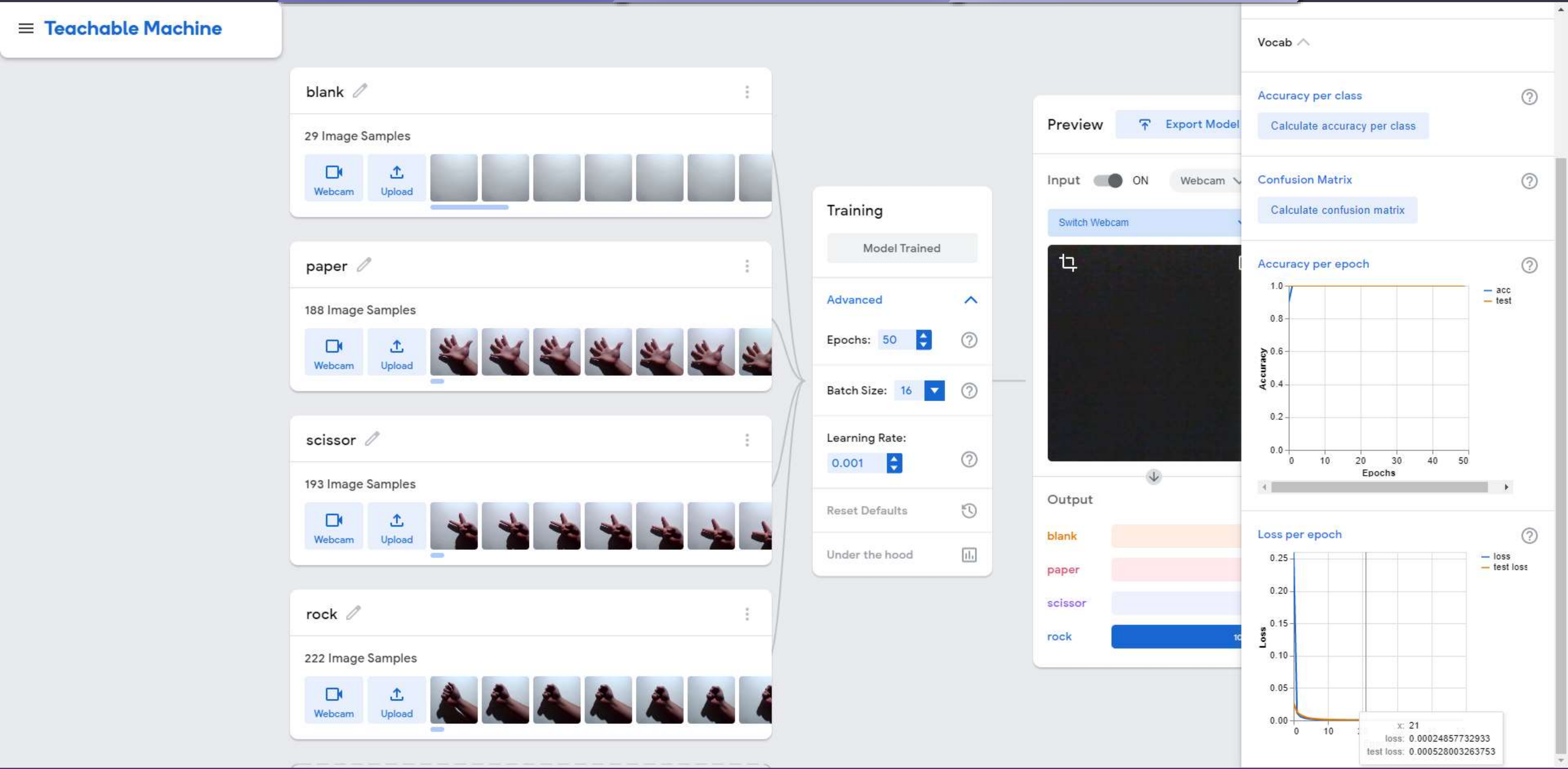
Gather Train Infer



Gather Train Infer

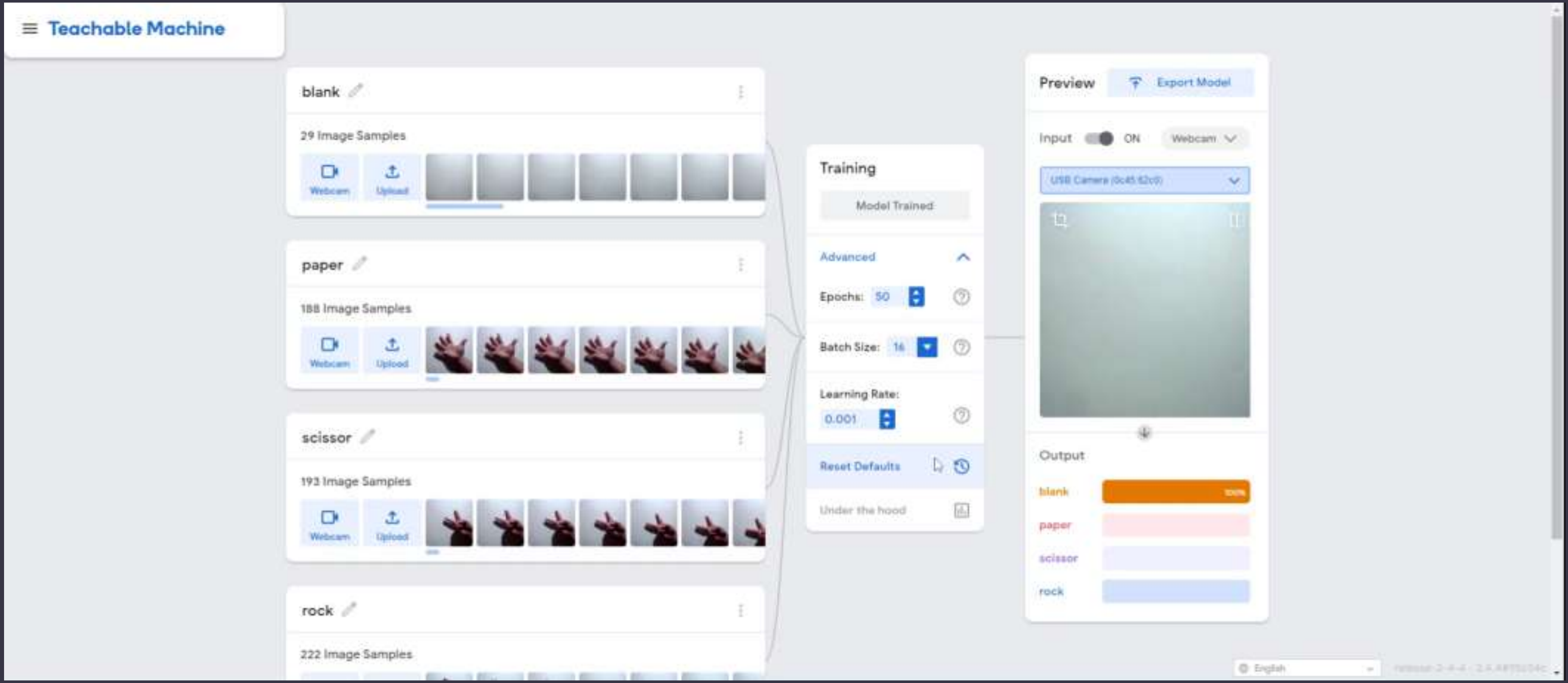


Gather Train Infer



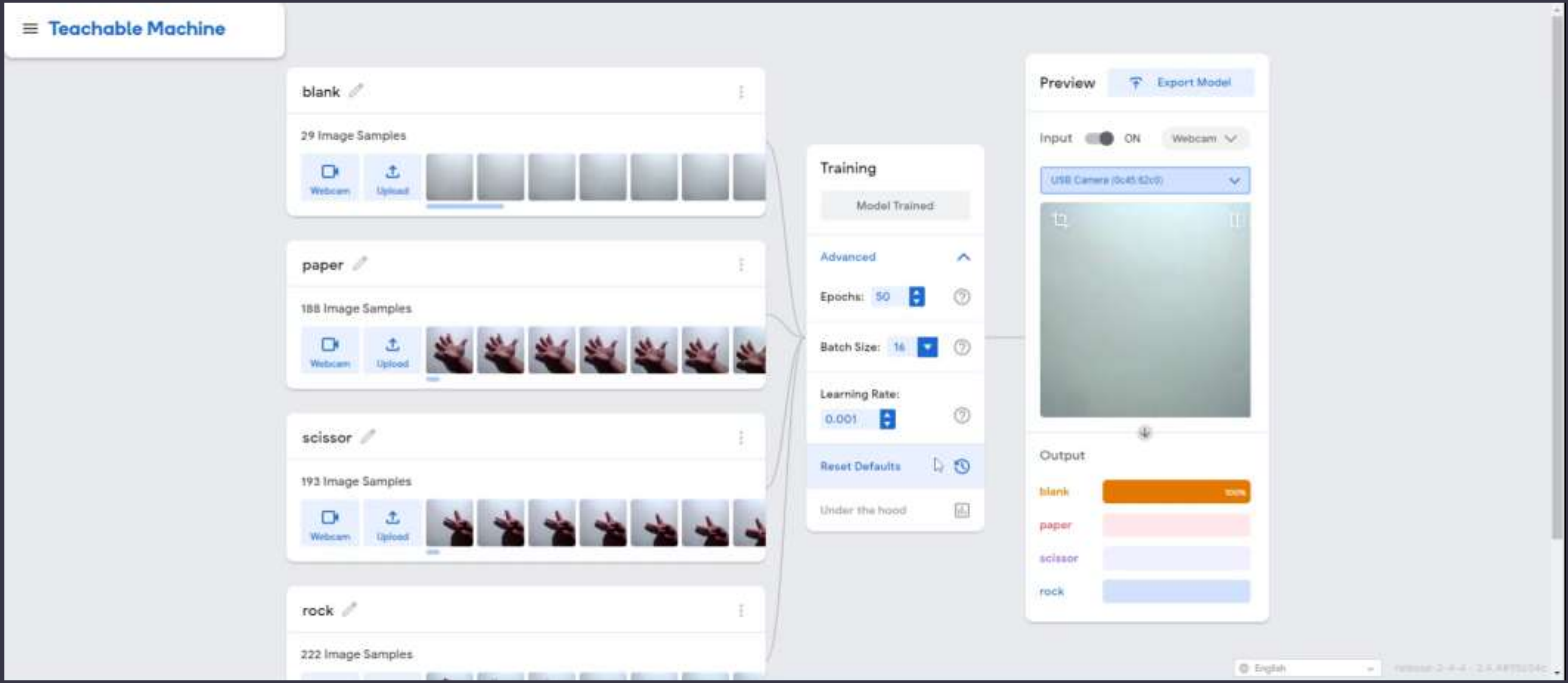
Gather | Train | **Infer**

Image inference/prediction



Gather → Train → **Infer**

Slanted image detection



Training details

Teachable Machine splits your samples into two buckets

- Training samples: 85% to train the model
  - How to correctly classify new samples into the classes
- Test samples: 15% never used to train the model, for checking
  - Used to check how well is the model on new, never-before-seen data

Training details

Underfit

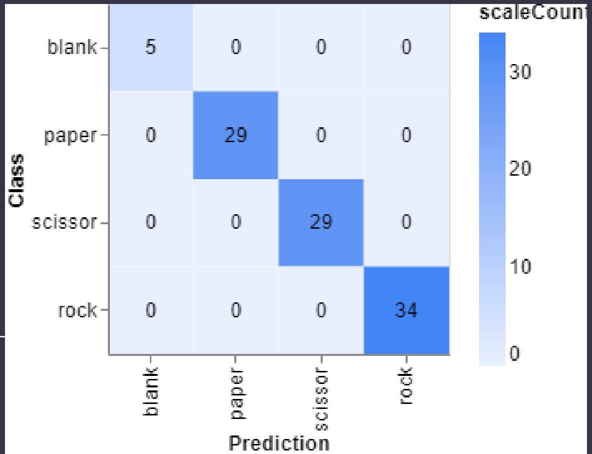
- Classifies poorly
- Model hasn't captured the complexity of the training samples

Overfit

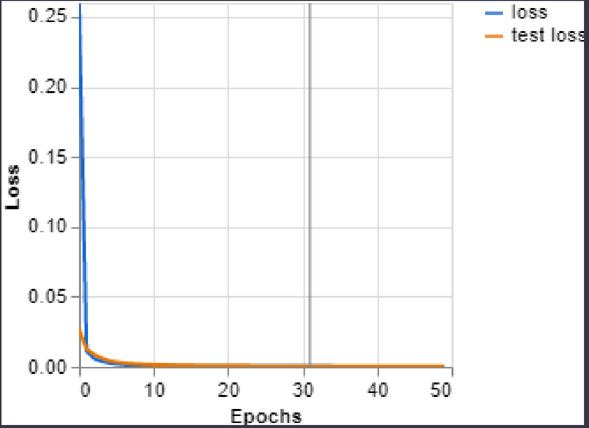
- Model classified the training samples too closely
- Fails to make correct classifications on the test samples
- Usually sample dropout is used (discard, throw away some training samples)

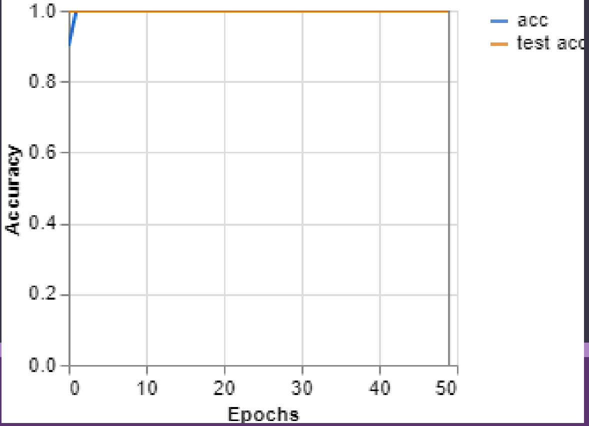
Epochs

- Every training sample has been fed through the model at least **once**
- For epochs = 50, the model you are training will work through the entire training dataset 50 times.

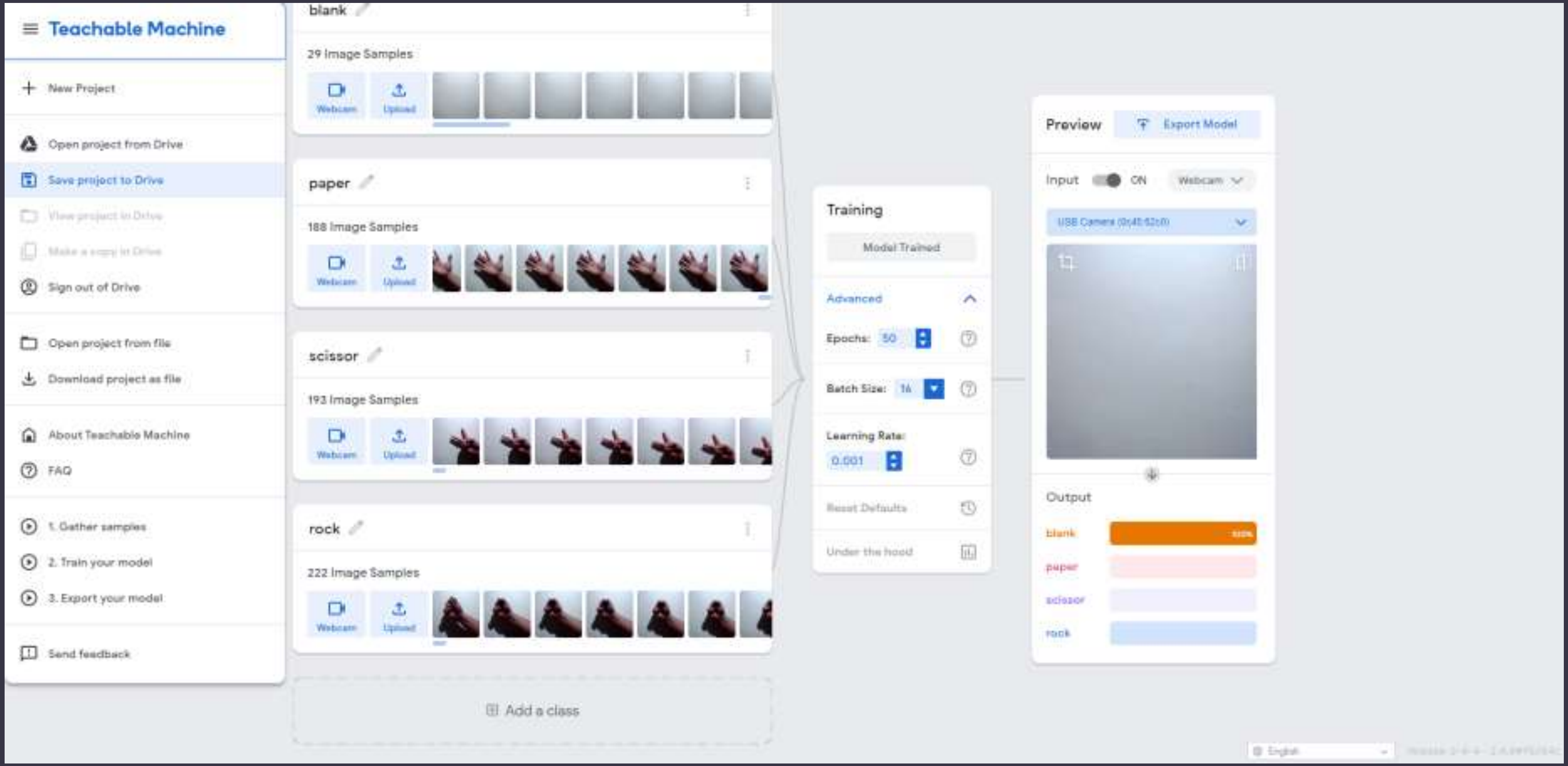


	blank	paper	scissor	rock
blank	5	0	0	0
paper	0	29	0	0
scissor	0	0	29	0
rock	0	0	0	34

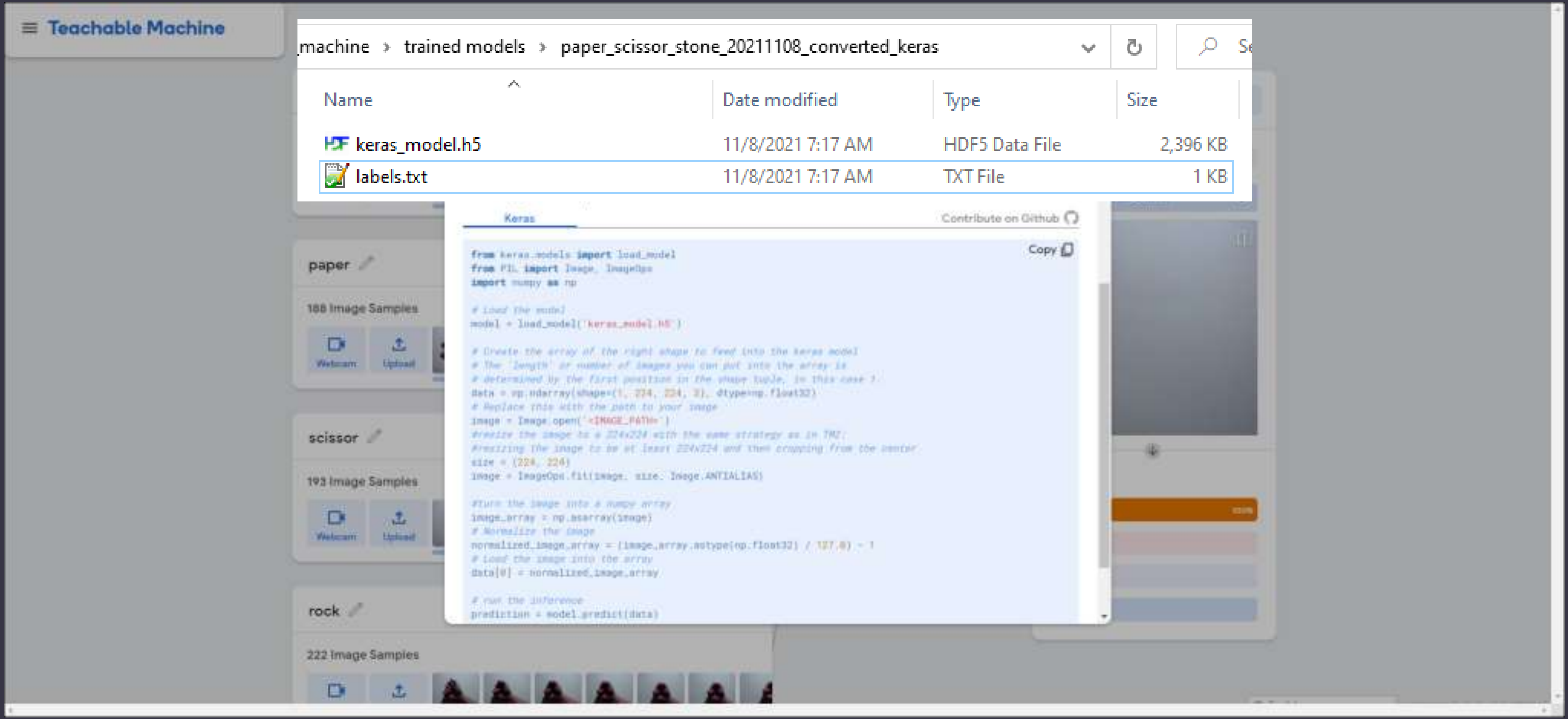




Export to google drive



Export trained model for GTM



Inference process on python

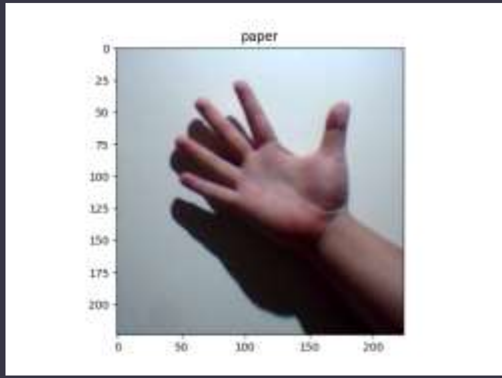
Load image → Trained keras model →

```
45
46    # run the inference
47    prediction = model.predict(data)
48    print(prediction)
49
```

TERMINAL   DEBUG CONSOLE   PROBLEMS

```
>>> print(prediction)
[[ 0.000  1.000  0.000  0.000]]
```

```
labels = ["blank", "paper", "scissor", "rock"]
```



TensorFlow

Sample code

gtm_rockpaperscissor.py ×

gtm_rockpaperscissor.py > ...

```python
"""gtm_rockpaperscissor.py"""

from keras.models import load_model
from PIL import Image, ImageOps
import numpy as np

# Load the model
model = load_model('keras_model.h5')

# Create the array of the right shape to feed into the keras model
# The 'length' or number of images you can put into the array is
# determined by the first position in the shape tuple, in this case 1.
data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)
# Replace this with the path to your image
image = Image.open('<IMAGE_PATH>')
#resize the image to a 224x224 with the same strategy as in TM2:
#resizing the image to be at least 224x224 and then cropping from the center
size = (224, 224)
image = ImageOps.fit(image, size, Image.ANTIALIAS)

#turn the image into a numpy array
image_array = np.asarray(image)
# Normalize the image
normalized_image_array = (image_array.astype(np.float32) / 127.0) - 1
# Load the image into the array
data[0] = normalized_image_array

# run the inference
prediction = model.predict(data)
print(prediction)
```

```python
# Function to determine label
def prediction_outcome(prediction, labels):
    # Find index with maximum probability
    max_index = np.argmax(prediction)
    # Treat probability with higher than 0.5 as identified
    if prediction.max() > 0.5:
        show_text = labels[max_index]
    else:
        show_text = "Not identified"
    print(show_text)
    return show_text


# Plot data and prediction
result = prediction_outcome(prediction, labels)
img = mpimg.imread(test_image)
imgplot = plt.imshow(img)
plt.title(result)
plt.show()
```

Extra notes

CPU/GPU version of trained model are sometimes not interchangeable

- Make sure training is done on similar setup
- Train on CPU => Infer on CPU
- Train on GPU => Infer on GPU
- ~~Train on GPU => Infer on CPU~~

The analogy to deep learning is that

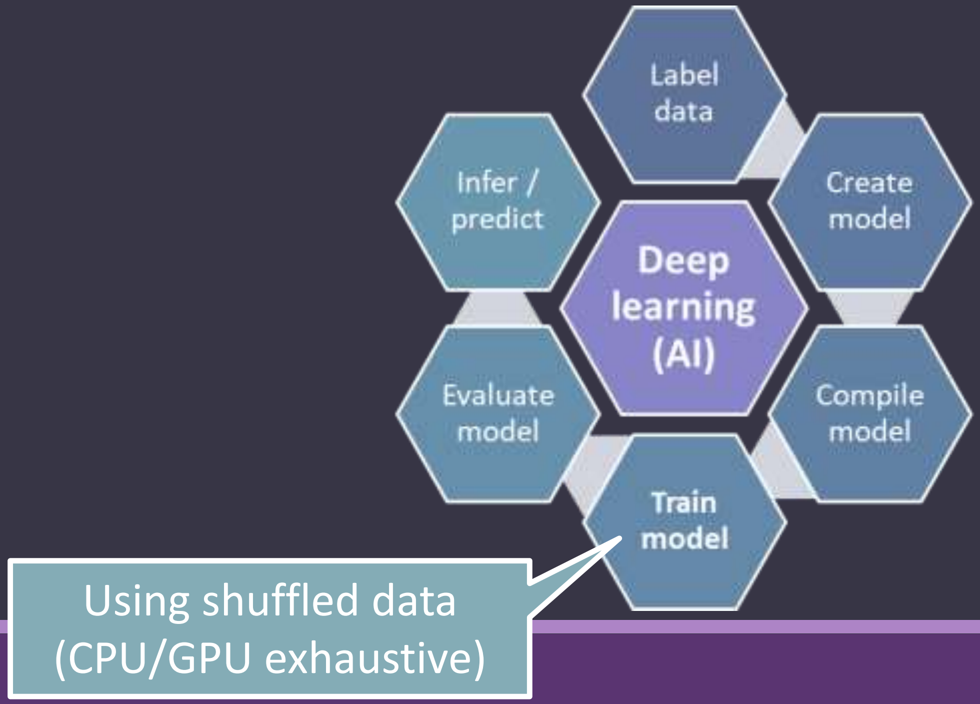
- the rocket engine is the deep learning models and
- the fuel is the huge amounts of data we can feed to these algorithms.

- Andrew Ng

- Co-founder and head of Google Brain
- Former Chief Scientist at Baidu
- Co-Founder of Coursera

Teachable machine

- GOOGLE INC.
- BRIDGE FROM ML TO DL
- TEACH MACHINES TO THINK (DL)



End of presentation

THANK YOU!

Bibliography

Middleton, M. (2021, February 8). *Deep Learning vs. Machine Learning—What's the Difference?* https://flatironschool.com/blog/deep-learning-vs-machine-learning/

Rowe, W., and Johnson, J. (2020, September 8). *Top Machine Learning Frameworks To Use in 2021*. BMC Blogs. https://www.bmc.com/blogs/machine-learning-ai-frameworks/

Copeland, M. (2016, July 29). *The Difference Between AI, Machine Learning, and Deep Learning? | NVIDIA Blog*. The Official NVIDIA Blog. https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

Bochkovskiy, A., Wang, C.-Y., and Liao, H.-Y. M. (2020). YOLOv4: Optimal Speed and Accuracy of Object Detection. *ArXiv:2004.10934 [Cs, Eess]*. http://arxiv.org/abs/2004.10934

Thompson, N. C., KRISTJAN GREENEWALD, KEEHEON LEE, and GABRIEL F. MANSO. (2021, September 24). *Deep Learning's Diminishing Returns*. IEEE Spectrum. https://spectrum.ieee.org/deep-learning-computational-cost

Mahapatra, S. (2019, January 22). *Why Deep Learning over Traditional Machine Learning?* Medium. https://towardsdatascience.com/why-deep-learning-is-needed-over-traditional-machine-learning-1b6a99177063

Garling, C. (2015, May). *Andrew Ng: Why 'Deep Learning' Is a Mandate for Humans, Not Just Machines | WIRED*. https://www.wired.com/brandlab/2015/05/andrew-ng-deep-learning-mandate-humans-not-just-machines/