APPLIED MATERIALS

KamaTech

AI Bootcamp Project Presentation

BOOTCAMP, 2023

IMAGE CLASSIFICATION MODEL (ALIENS GROUP)

PROJECT AT APPLIED MATERIALS

BOOTCAMP, 2023

OVERVIEW:

Our image classification application employs advanced machine learning techniques to accurately categorize images into 13 distinct classes. Built upon the robust CIFAR-10 dataset and some of the CIFAR-100 dataset, which comprises a diverse range of images, our app provides intelligent classification capabilities that cater to various visual domains.

By integrating a range of powerful tools, including deep learning and transfer learning, we empower our app to make accurate predictions

STAGES:

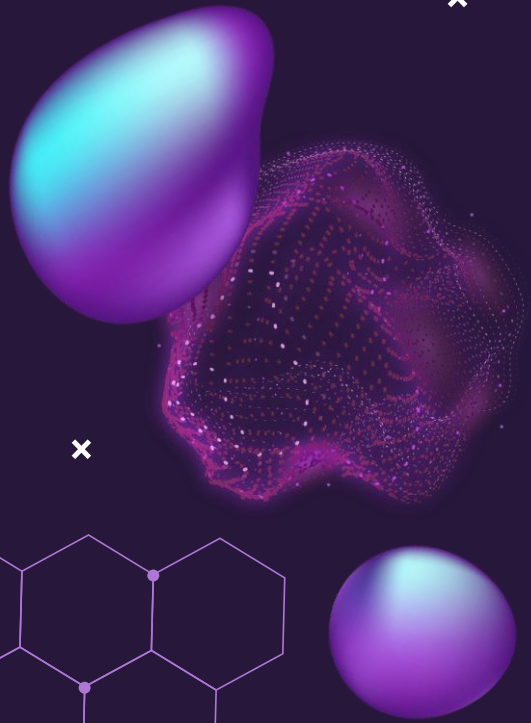
01 PREPARE DATA

02 TRAIN MODEL

03 VISUALIZE

04 DEPLOYING & MONITIORING


01
PREPARING THE DATA



“You can have data without information, but you cannot have information without data.”

— Daniel Keys Moran.

STEPS INCLUDED:

DOWNLOAD

Data from different sources

RESIZING+ normilization

Each additional picture has to have the same size as cifar images.
And needs to be normilized

AUGMENTATION

In order to have balanced data.

IMG -> NP ARRAY!

Our model will be trained on an NP array.

Data Source:

83% CIFAR-10

16% CIFAR-100

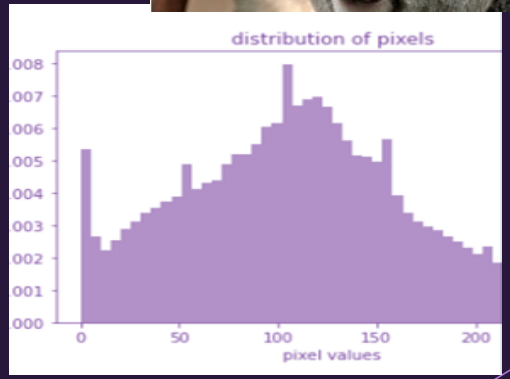
1% Additional pictures

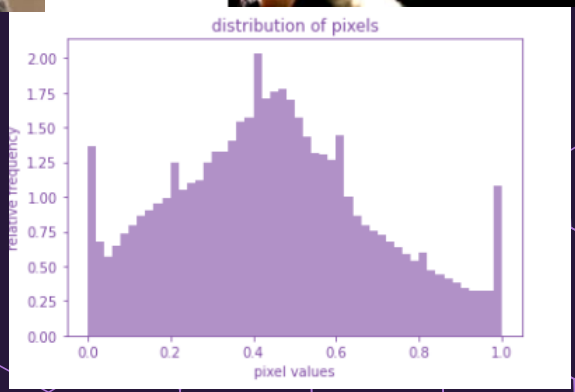
Normilization:

×

What is image normalization?

Image normalization scales pixel values from [0, 255] to [0, 1] by dividing each pixel by 255.





Why is image normalization crucial for deep learning models?

Normalization can help training of our neural networks as the different features are on a similar scale

which helps to stabilize the gradient descent step

allowing us to use larger learning rates or help models converge faster for a given learning rate.

Resampling:

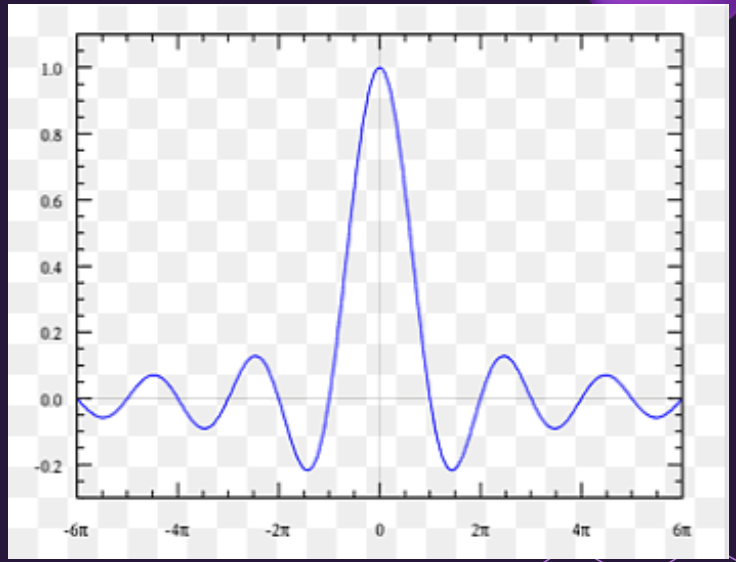
In order to train a neural network effectively we need to have all the images the same size

Because the cifar10 images are 32X32 we need to resample the images which are added to the training process.

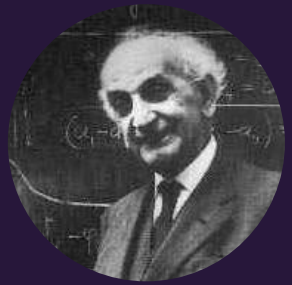
we used the Lanczos resize method

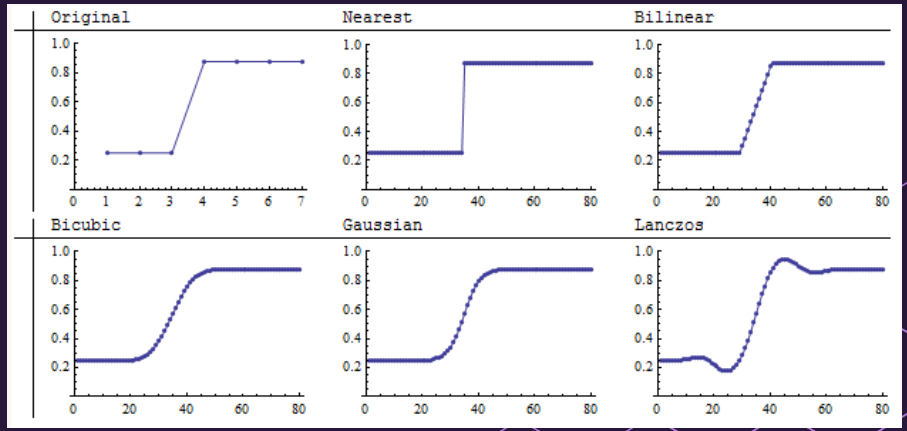
How does Lanczos work?

Lanczos resampling uses the sinc function to blend nearby pixel values based on their distances from the target pixel. This weighted averaging process ensures that fine details are preserved and artifacts are minimized. The resulting downscaled image aims to maintain image quality while reducing its size.



Lanczos in contrast to other interpolation methods





Our dataset consists of:

Cifar10:
10 classes of 5,000 images

Cifar100:
3 classes of 2,500 images

The data is unbalanced!

DATA AUGMENTATION

THE SOLUTION:

Doubling the number of samples for each class from Cifar100 by rotating each image from the dataset

THE RESULT:

A completely balanced data set.

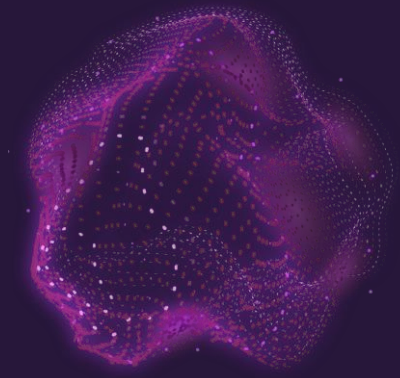
Data augmentation

Data augmentation involves applying various transformations and modifications to the existing dataset to create new instances of data. The goal is to increase the diversity of the dataset and help the model generalize better

Data augmentation offers several advantages in machine learning

- Enhanced Generalization
- Better handling of unexpected changes and noise
- Reduced Overfitting
- Addressing Imbalance
- Optimal Resource Use
- Better Results

Data format:



Npy files

Which have many advantages:

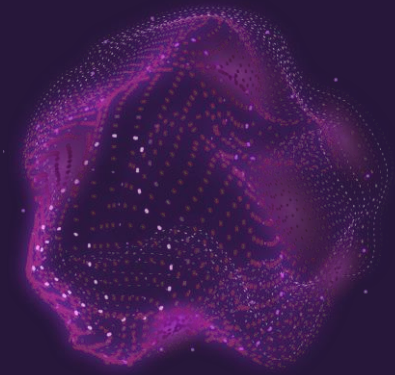
- Fast Readability
- Portability
- Memory Efficiency
- Supports Training Process
- Customization

We have one problem:

- The Cifar10 dataset is old (since 2008) The cars, airplane, trucks and ships look different nowadays.

- our data includes only 60,000 images for ten categories which is not much for very accurate predictions

The solution:



Adding a feature that allows users to upload their own images, and our system, powered by a pre-trained ResNet50 model which is based on the large imagenet dataset, classifies these images into predefined categories

14,197,122 images

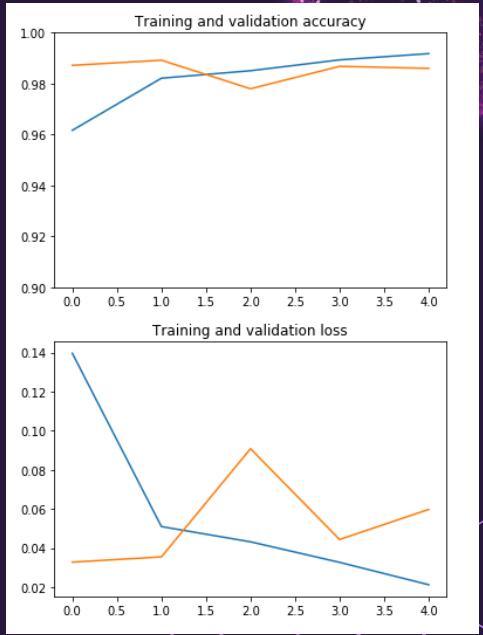
IMAGENET

Link to the app

Why use resnet50?

ResNet-50 is a powerful deep learning model known for its:

- 50-layer deep neural network architecture.
- Pre-training on the extensive ImageNet dataset for feature learning.
- Versatility for transfer learning across various computer vision tasks.
- excels in image classification and is widely used in research and real-world applications because of its accuracy and adaptability



In Summary:

The ResNet-50 model is well-suited for preprocessing due to its high accuracy

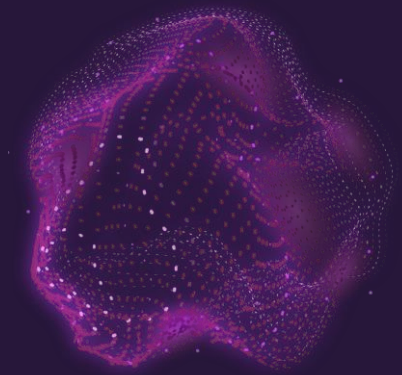
it's more practical to employ a simpler model for the actual classification task

primarily because it demands extensive computational resources.

Almost done...
but oops one more problem!

The imagenet dataset has 1,000 classes and cifar10 has only 10

Many classes in imagenet are subclasses of classes in cifar10



For example:

In cifar10 there is an airplane class

But in imagenet there are numerous different classes of different kinds of airplanes

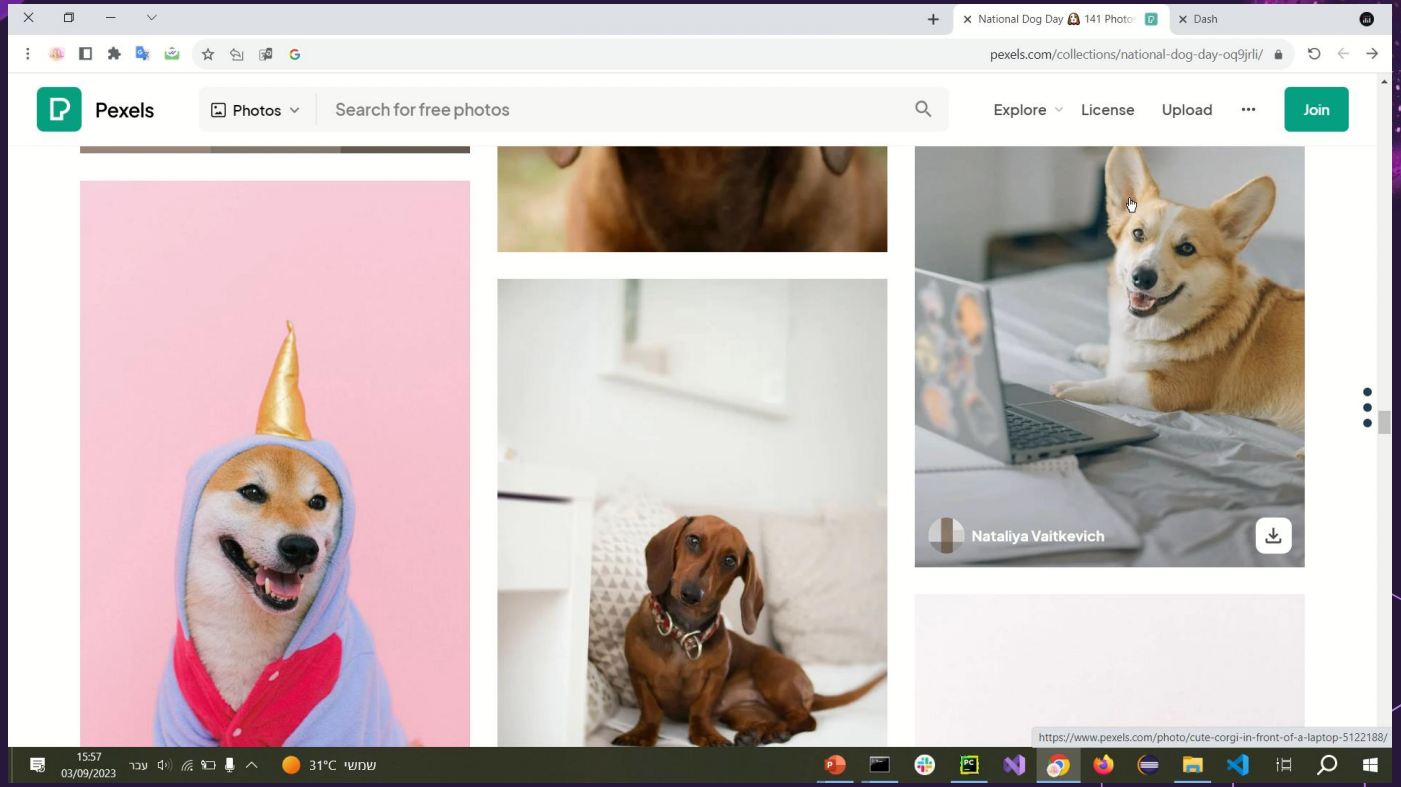
```
narrowbody aircraft, narrow-body aircraft, narrow-body
widebody aircraft, wide-body aircraft, wide-body, twin-aisle airplane
```

The solution:

A python script that gets a txt file in the following format and maps the imagenet classes to match the cifar10 classes

```
-----------------------------------n03174079: delta wing
-----------------------------------n03335030: fighter, fighter aircraft, attack aircraft
---------------------------------------n03577672: interceptor
---------------------------------------n03608074: kamikaze
---------------------------------------n04308397: stealth fighter
-----------------------------------n03490784: hangar queen
-----------------------------------n03595860: jet, jet plane, jet-propelled plane
---------------------------------------n03321419: fanjet, fan-jet, turbofan, turbojet
---------------------------------------n03596543: jetliner
---------------------------------------n03604311: jumbojet, jumbo jet
---------------------------------------n04503499: twinjet
-----------------------------------n03783873: monoplane
-----------------------------------n03798610: multiengine airplane, multiengine plane
-----------------------------------n04012084: propeller plane
```

Our GUI


National Dog Day
141 Photo
Dash
pexels.com/collections/national-dog-day-oq9jrli/
Pexels
Photos
Search for free photos
Explore
License
Upload
Join
Nataliya Vaitkevich
https://www.pexels.com/photo/cute-corgi-in-front-of-a-laptop-5122188/
15:57
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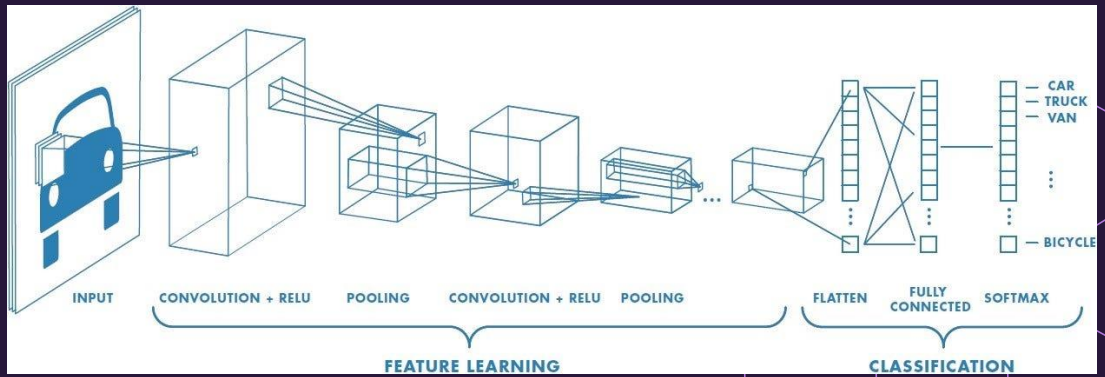
GENERAL EXPLANATION ABOUT CNN

(NOGAH GROUP)

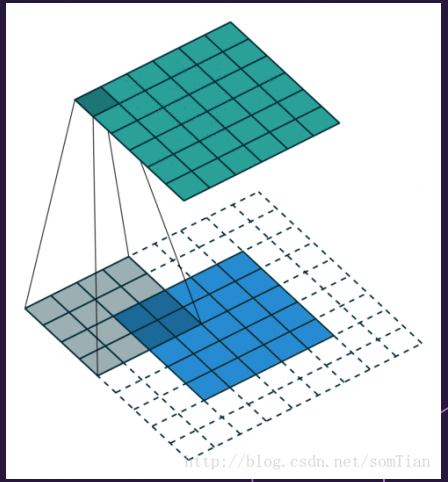
CNN MAIN LAYERS

- Convolution layer
- ReLU layer
- Dropout Layer
- Max Pooling Layer
- Fully Connected Layer
- SoftMax Layer



CONVOLUTION LAYER

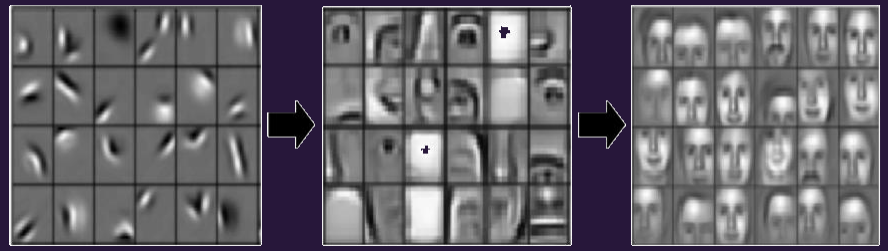
A convolutional layer is the main building block of a CNN. It contains a set of filters (or kernels), parameters of which are to be learned throughout the training.
Convolutional layers apply a convolution operation to the input, passing the result to the next layer. A convolution converts all the pixels in its receptive field into a single value.



CONVOLUTION KERNELS

The activation maps output by convolutional layers can be inspected to understand exactly what features detected for a given input image.

Visualizing the filters within a learned convolutional neural network can provide insight into how the model works.



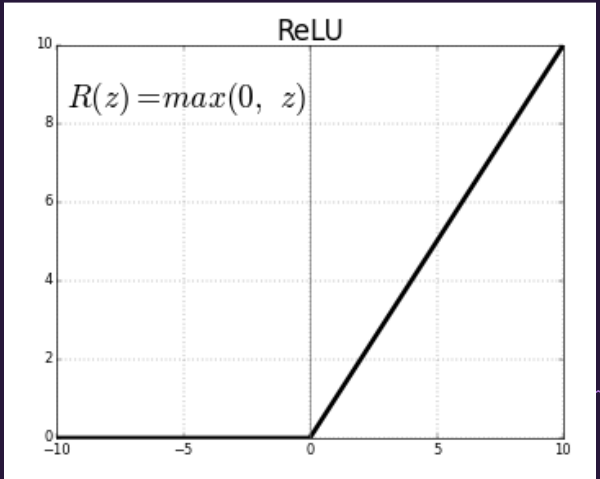
Edges, dark spots | Eyes, ears, nose | Facial structure

RELU LAYER

After each convolution operation, a CNN applies a Rectified Linear Unit (ReLU) transformation to the feature map, introducing nonlinearity to the model.

The purpose of applying the ReLU function is to increase the non-linearity in our images, in order to make up for the linearity that we might impose an image when we put it through the convolution operation.

The ReLU is the most commonly used activation function in deep learning models.

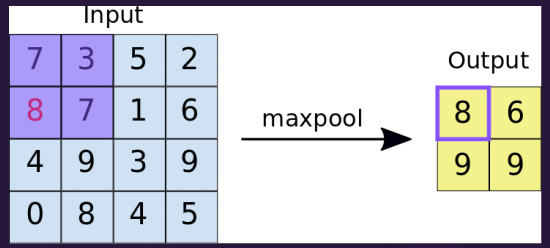


MAX POOLING LAYER

Pooling layers are used to reduce the dimensions of the feature maps. It summarizes the features present in a region of the feature map generated by a convolution layer. So further operations are performed on summarized features instead of precisely positioned features generated by the convolution layer.

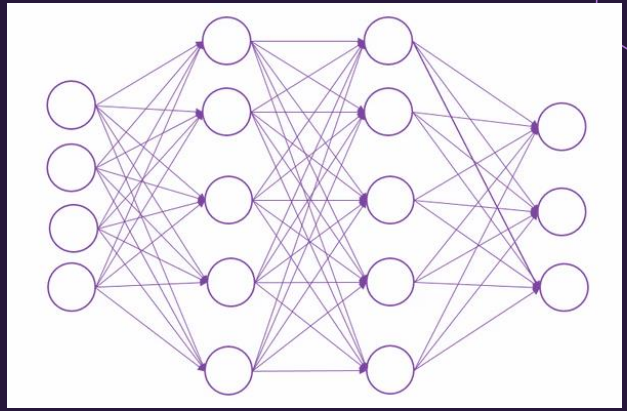
This makes the model more robust to variations in the position of the features in the input image.

The output after max-pooling layer would be a feature map containing the most prominent features of the previous feature map.



DROPOUT LAYER

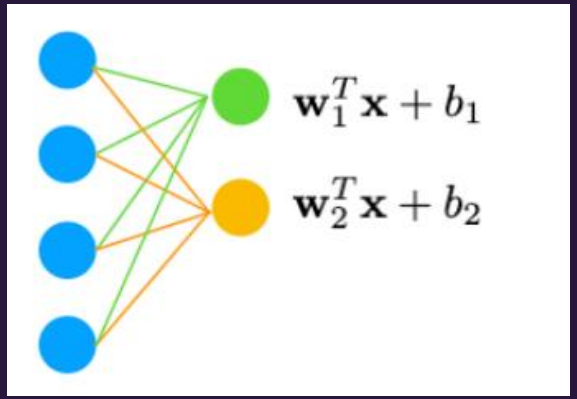
Dropout is a regularization technique for neural network models, where randomly selected neurons are ignored during training. This means that their contribution to the activation of downstream neurons is temporally removed on the forward pass, and any weight updates are not applied to the neuron on the backward pass.
The effect is that the network becomes less sensitive to the specific weights of neurons. This, in turn, results in a network capable of better generalization and less likely to overfit the training data.



FULLY CONNECTED LAYER

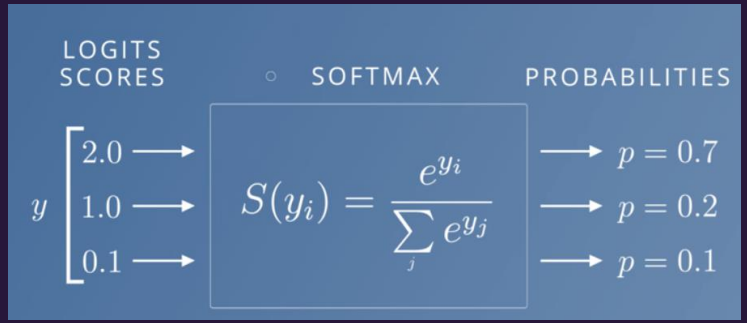
A fully connected layer in neural network is where all the inputs from one layer are connected to every activation unit of the next layer. As a result, all possible connections layer-to-layer are present, meaning every input of the input vector influences every output of the output vector. However, not all weights affect all outputs.

The Fully connected layer is used for classifying the input image into a label. It connects the information extracted from the previous steps to the output layer and eventually classifies the input into the desired label.



SOFTMAX LAYER

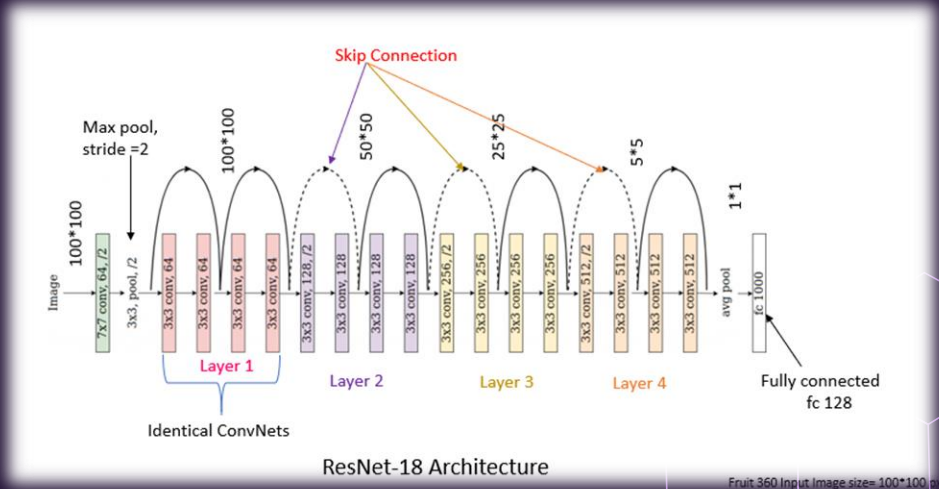
The Softmax function is a crucial component in the output layer of CNNs for classification tasks. It transforms the raw scores produced by the network into a meaningful probability distribution over classes, making it easier to interpret and use the model's predictions.



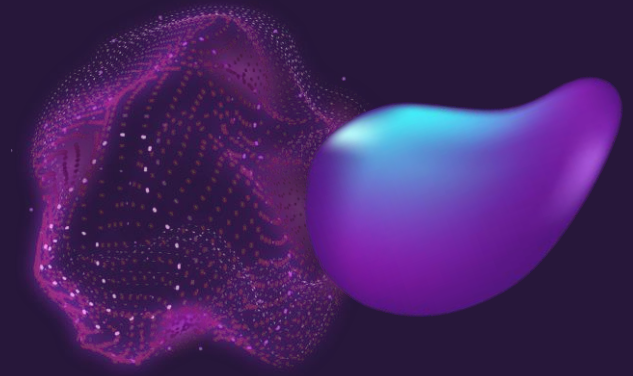
RESNET

Residual Network (ResNet) is a deep learning model used for computer vision applications. It is a Convolutional Neural Network (CNN) architecture designed to support hundreds or thousands of convolutional layers.

Previous CNN architectures were not able to scale to a large number of layers, which resulted in limited performance. However, when adding more layers, researchers faced the “vanishing gradient” problem.

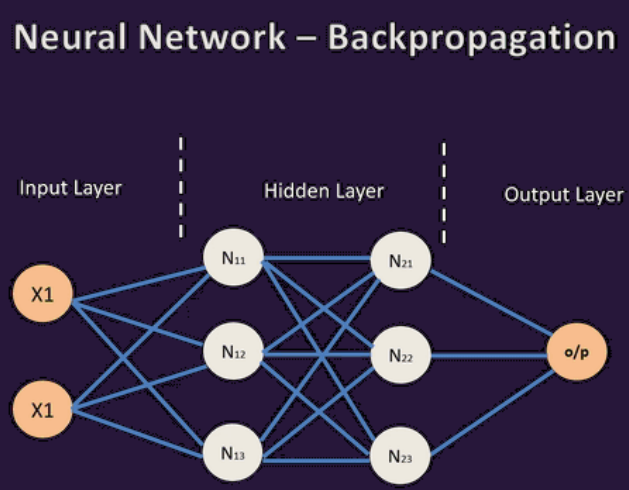


BACKPROPAGATION



BACKPROPAGATION

Backpropagation is a fundamental technique used in training neural networks. It involves the iterative adjustment of weights within a network to minimize errors and enhance its ability to map inputs to outputs accurately. By comprehending the essence of backpropagation, we can gain insights into how neural networks learn and improve their predictions.



THE IMPLEMENTATION

To implement backpropagation, the chain rule of differentiation plays a pivotal role. This mathematical concept allows us to efficiently compute derivatives of the loss function with respect to the network's weights, particularly in the context of a neural network's layered architecture. The chain rule unravels how changes in weights influence the overall loss, providing crucial insights into how to minimize it. This intricate process serves as the foundation for refining the network's weights and improving its performance.

$$\frac{dy}{dx} = \frac{dy}{du}\frac{du}{dx}$$

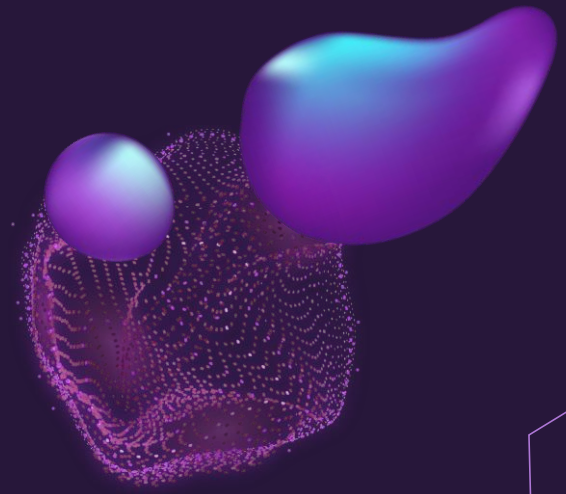
$$\frac{d^2y}{dx^2} = \frac{d^2y}{du^2}\left(\frac{du}{dx}\right)^2 + \frac{dy}{du}\frac{d^2u}{dx^2}$$

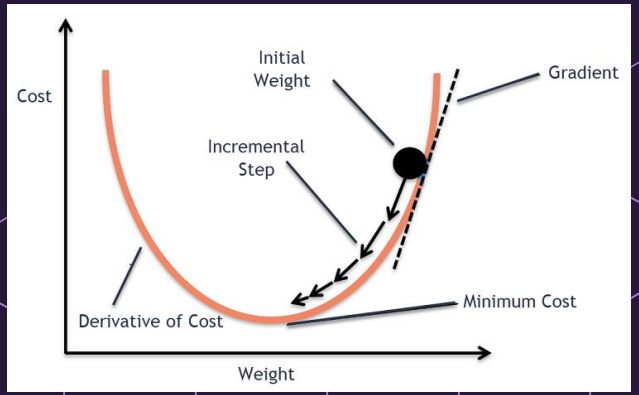
$$\frac{d^3y}{dx^3} = \frac{d^3y}{du^3}\left(\frac{du}{dx}\right)^3 + 3\,\frac{d^2y}{du^2}\frac{du}{dx}\frac{d^2u}{dx^2} + \frac{dy}{du}\frac{d^3u}{dx^3}$$

$$\frac{d^4y}{dx^4} = \frac{d^4y}{du^4}\left(\frac{du}{dx}\right)^4 + 6\,\frac{d^3y}{du^3}\left(\frac{du}{dx}\right)^2\frac{d^2u}{dx^2} + \frac{d^2y}{du^2}\left(4\,\frac{du}{dx}\frac{d^3u}{dx^3} + 3\left(\frac{d^2u}{dx^2}\right)^2\right) + \frac{dy}{du}\frac{d^4u}{dx^4}.$$

GRADIENT DESCENT

Gradient Descent (GD) is a commonly used optimization technique that leverages backpropagation. GD updates the weights by analyzing the gradients of the loss function with respect to the weights. Through backpropagation, GD identifies which weights should be increased or decreased to minimize the loss. This process is performed in a reverse order, as adjustments to earlier layers affect subsequent ones due to the interconnected nature of neural networks.





Model Construction and Training Process (Bereshit GROUP)

BOOTCAMP, 2023

STAGES:

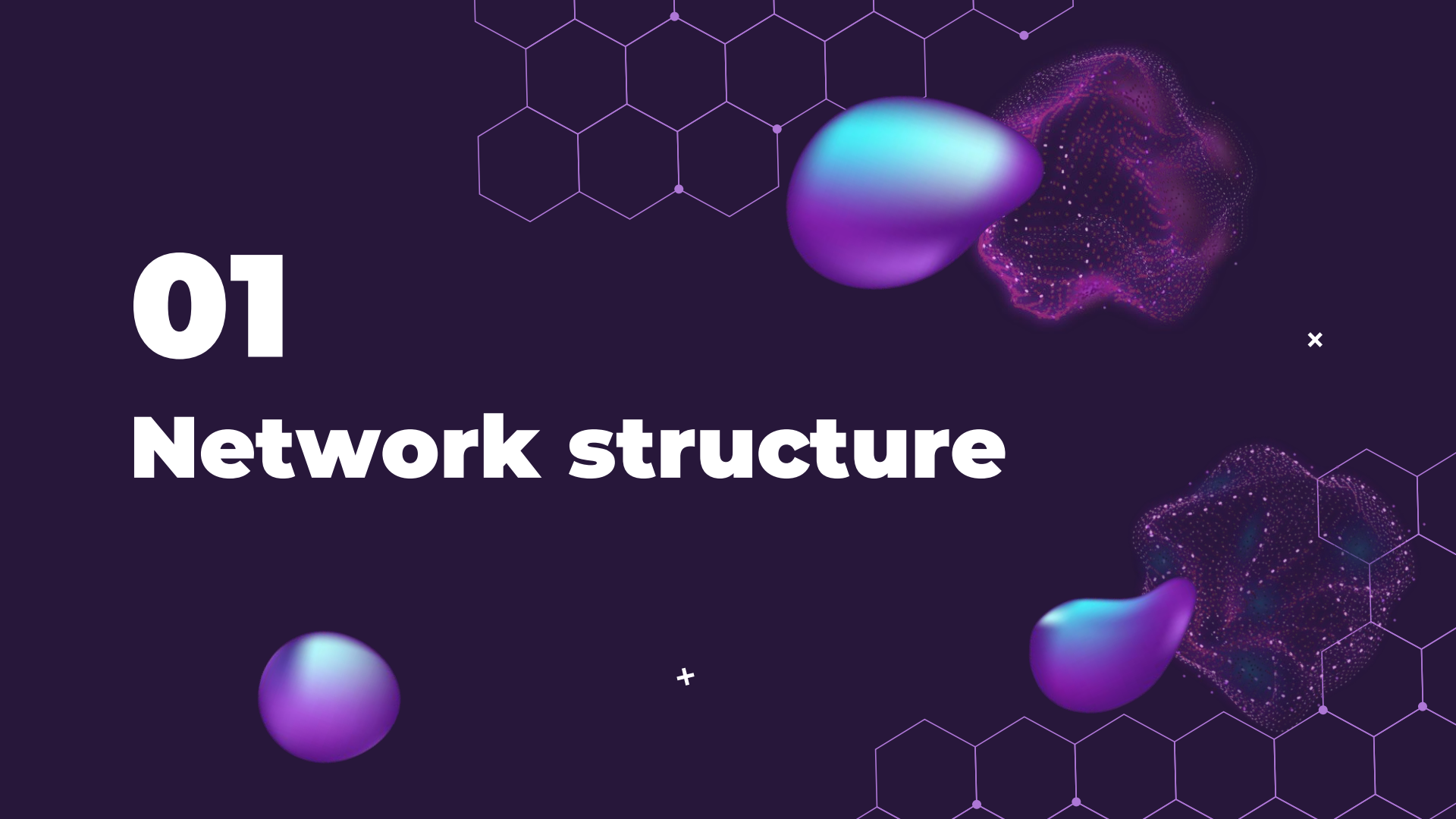
01 The network structure

02 Training process

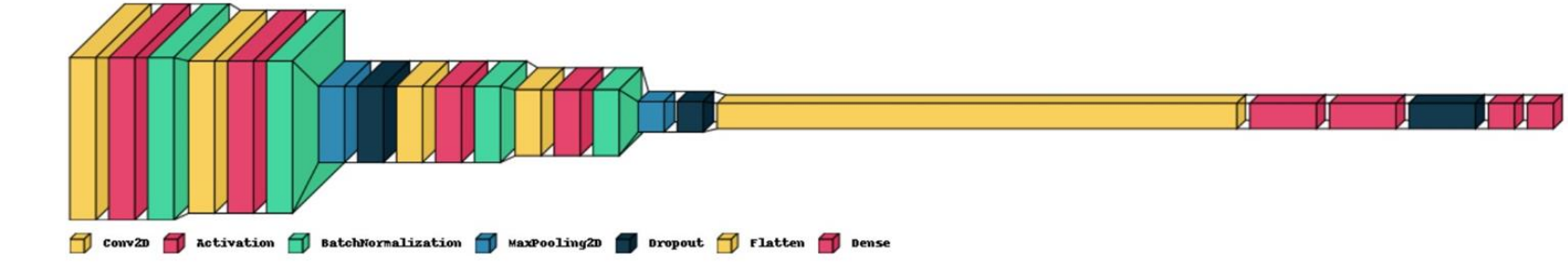
03 Out of Distribution

01

Network structure



Model architecture



Conv2D->Relu->BatchNormalization->Conv2D->Relu->BatchNormalization->MaxPooling2D->Dropout->Conv2D->

Relu-> BatchNormalization->Conv2D->Relu->BatchNormalization->MaxPooling2D->Dropout->Flatten->Dense-> Relu-

>Dropout-> Dense->SoftMax

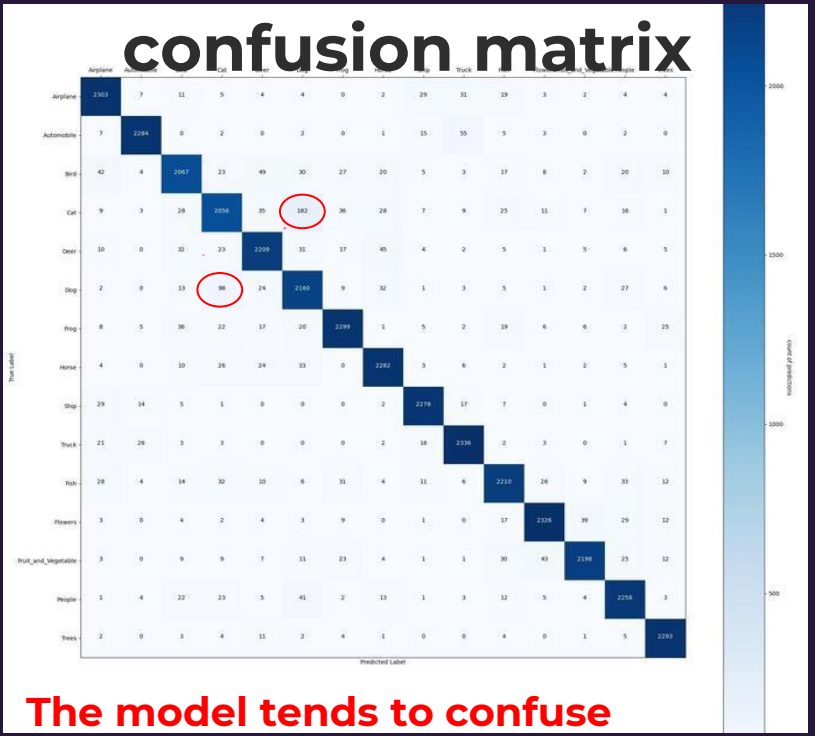
```
model.add(Conv2D(64, (3, 3), padding='same',input_shape=self.input_shape))  # 32*32*64
model.add(Activation('relu'))  # 32*32*64
model.add(BatchNormalization())  # 32*32*64
model.add(Conv2D(64, (3, 3)))  # 32*32*1 ->  30*30*64
model.add(Activation('relu'))  # 30*30*64
model.add(BatchNormalization())  # 30*30*64
model.add(MaxPooling2D(pool_size=(2, 2)))  # 15*15*64
model.add(Dropout(0.25))  # 15*15*64
model.add(Conv2D(128, (3, 3), padding='same'))   # 15*15*1 -> 15*15*128
model.add(Activation('relu'))  # 15*15*128
model.add(BatchNormalization())  # 15*15*128
model.add(Conv2D(128, (3, 3)))  # 15*15*1 -> 13*13*128
model.add(Activation('relu'))  # 13*13*128
model.add(BatchNormalization())  # 13*13*128
model.add(MaxPooling2D(pool_size=(2, 2)))  # 6*6*128
model.add(Dropout(0.25))  # 6*6*128
model.add(Flatten())  # 4,608*1*1
model.add(Dense(512, kernel_regularizer=l2(0.001)))  # 512*1*1
model.add(Activation('relu'))  # 512*1*1
model.add(Dropout(0.5))  # 512*1*1
model.add(Dense(self.num_classes))  # 10*1*1
model.add(Activation('softmax'))  # 10*1*1
```

02

Training process

Visualization

confusion matrix



The model tends to confuse

dogs vs. cats

printing of epochs

```
Epoch 1/150
  15/3375 [..............................] - ETA: 26s - loss: 6.3600 - accuracy: 0.0708
2023-08-01 13:08:32.209989: E tensorflow/core/grappler/optimizers/meta_optimizer.cc:954] layout failed: INVALID_ARGUMENT: Size of values 0 does n
3375/3375 [==============================] - 26s 8ms/step - loss: 2.3738 - accuracy: 0.2153 - val_loss: 1.8230 - val_accuracy: 0.4084
Epoch 2/150
3375/3375 [==============================] - 22s 7ms/step - loss: 1.7779 - accuracy: 0.4123 - val_loss: 1.4951 - val_accuracy: 0.5083
Epoch 3/150
3375/3375 [==============================] - 21s 6ms/step - loss: 1.5478 - accuracy: 0.4889 - val_loss: 1.3307 - val_accuracy: 0.5616
Epoch 4/150
3375/3375 [==============================] - 22s 6ms/step - loss: 1.3954 - accuracy: 0.5437 - val_loss: 1.1847 - val_accuracy: 0.6101
Epoch 5/150
3375/3375 [==============================] - 24s 7ms/step - loss: 1.2829 - accuracy: 0.5828 - val_loss: 1.1345 - val_accuracy: 0.6248
Epoch 6/150
3375/3375 [==============================] - 22s 7ms/step - loss: 1.1926 - accuracy: 0.6119 - val_loss: 1.0064 - val_accuracy: 0.6667
Epoch 7/150
3375/3375 [==============================] - 21s 6ms/step - loss: 1.1176 - accuracy: 0.6358 - val_loss: 0.9862 - val_accuracy: 0.6733
Epoch 8/150
3375/3375 [==============================] - 22s 7ms/step - loss: 1.0546 - accuracy: 0.6567 - val_loss: 0.8875 - val_accuracy: 0.7067
Epoch 9/150
3375/3375 [==============================] - 22s 6ms/step - loss: 1.0010 - accuracy: 0.6757 - val_loss: 0.8343 - val_accuracy: 0.7244
Epoch 10/150
3375/3375 [==============================] - 21s 6ms/step - loss: 0.9536 - accuracy: 0.6887 - val_loss: 0.8282 - val_accuracy: 0.7260
Epoch 11/150
3375/3375 [==============================] - 22s 6ms/step - loss: 0.9100 - accuracy: 0.7016 - val_loss: 0.7494 - val_accuracy: 0.7525
Epoch 12/150
3375/3375 [==============================] - 22s 6ms/step - loss: 0.8713 - accuracy: 0.7151 - val_loss: 0.7713 - val_accuracy: 0.7473
Epoch 13/150
3375/3375 [==============================] - 24s 7ms/step - loss: 0.8377 - accuracy: 0.7261 - val_loss: 0.7471 - val_accuracy: 0.7514
...
Epoch 149/150
3375/3375 [==============================] - 22s 6ms/step - loss: 0.2067 - accuracy: 0.9304 - val_loss: 0.2829 - val_accuracy: 0.9327
Epoch 150/150
3375/3375 [==============================] - 24s 7ms/step - loss: 0.2014 - accuracy: 0.9329 - val_loss: 0.2862 - val_accuracy: 0.9323
```

The final loss and accuracy

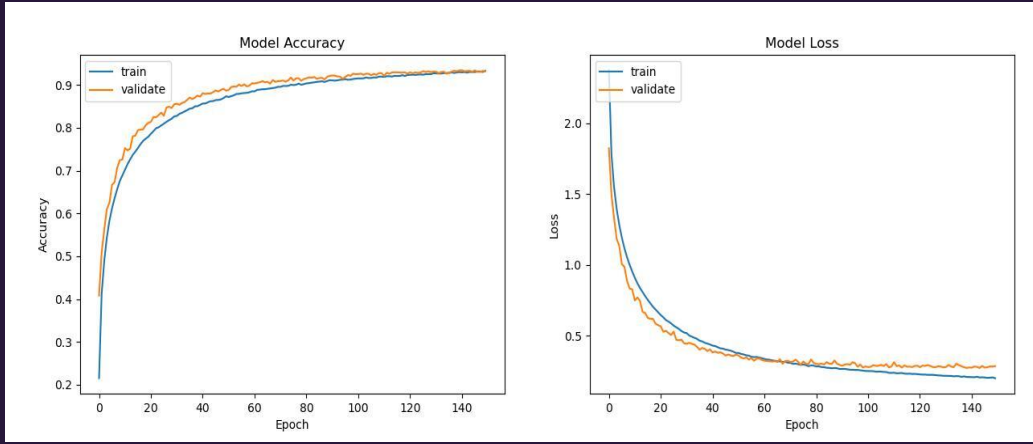
```
Test loss: 0.29154843091964720
Test accuracy: 0.93219447135925290
```

Visualization

Classification Report

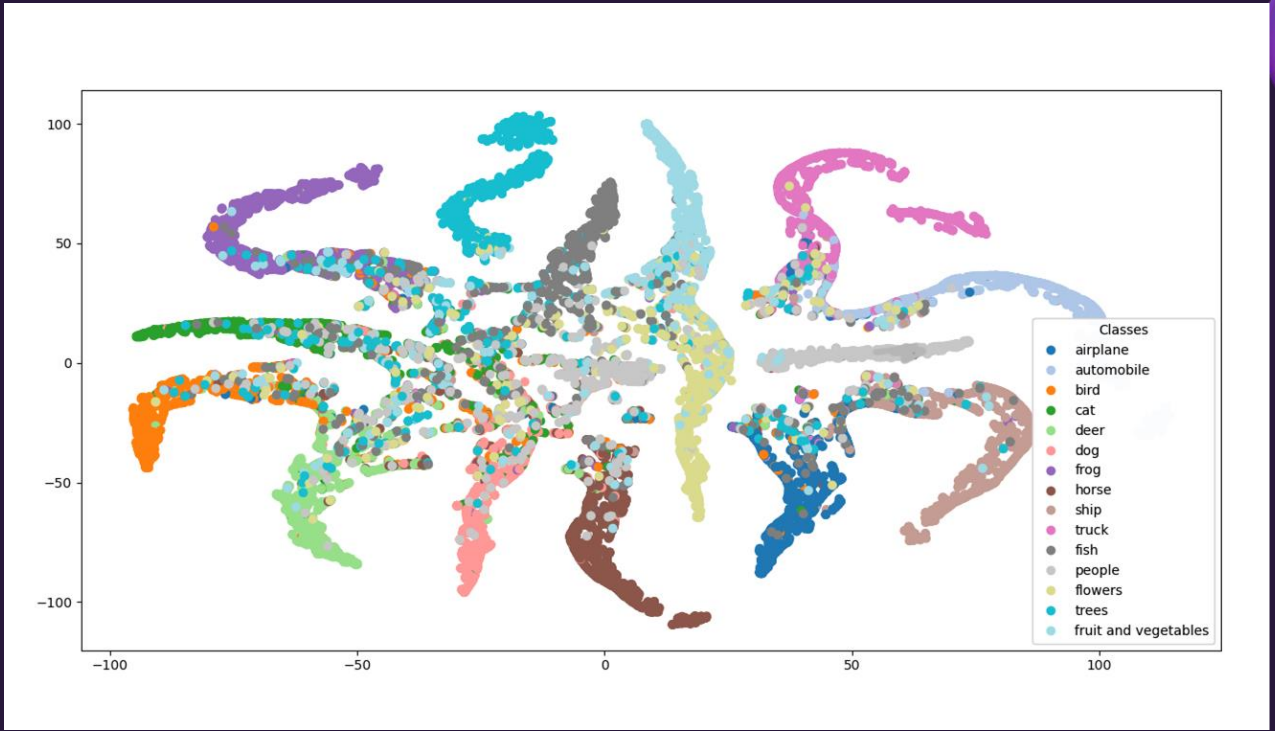
	precision	recall	f1-score	support
0	0.93	0.95	0.94	2428
1	0.97	0.96	0.97	2376
2	0.92	0.89	0.90	2327
3	0.88	0.84	0.86	2453
4	0.92	0.92	0.92	2395
5	0.86	0.91	0.88	2383
6	0.94	0.93	0.93	2473
7	0.94	0.95	0.94	2399
8	0.96	0.97	0.96	2358
9	0.94	0.97	0.95	2420
10	0.93	0.91	0.92	2436
11	0.95	0.95	0.95	2449
12	0.96	0.93	0.94	2376
13	0.93	0.94	0.93	2397
14	0.96	0.98	0.97	2330
accuracy			0.93	36000
macro avg	0.93	0.93	0.93	36000
weighted avg	0.93	0.93	0.93	36000

accuracy vs. loss



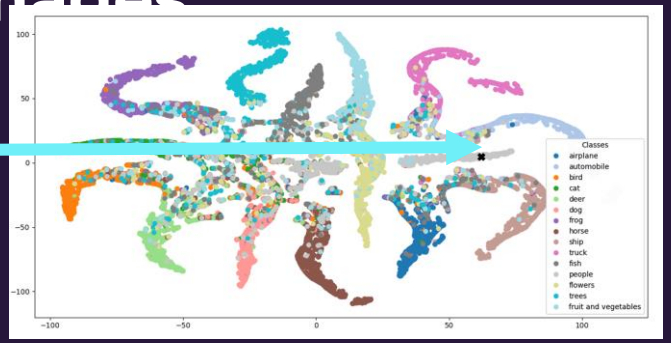
Visualization

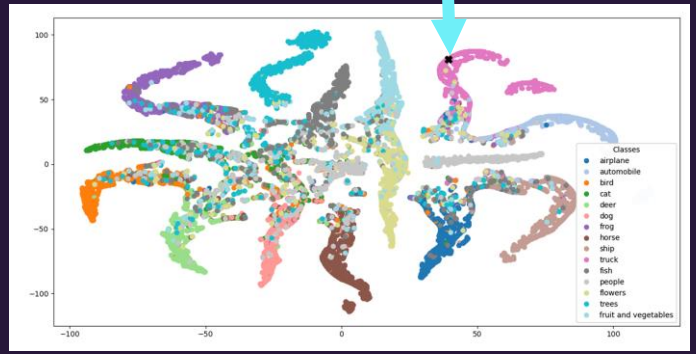
T-sne

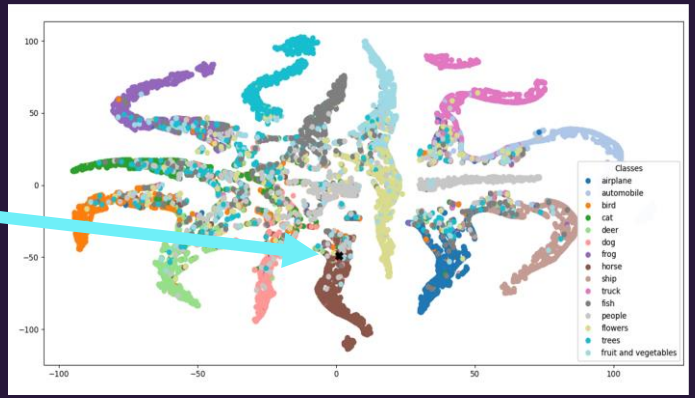


Visualization

T-sne new images







03

Out of Distribution

e.g.

Welcome to our Image Classifier

Upload Image

Sorry, your image label is not in our training set

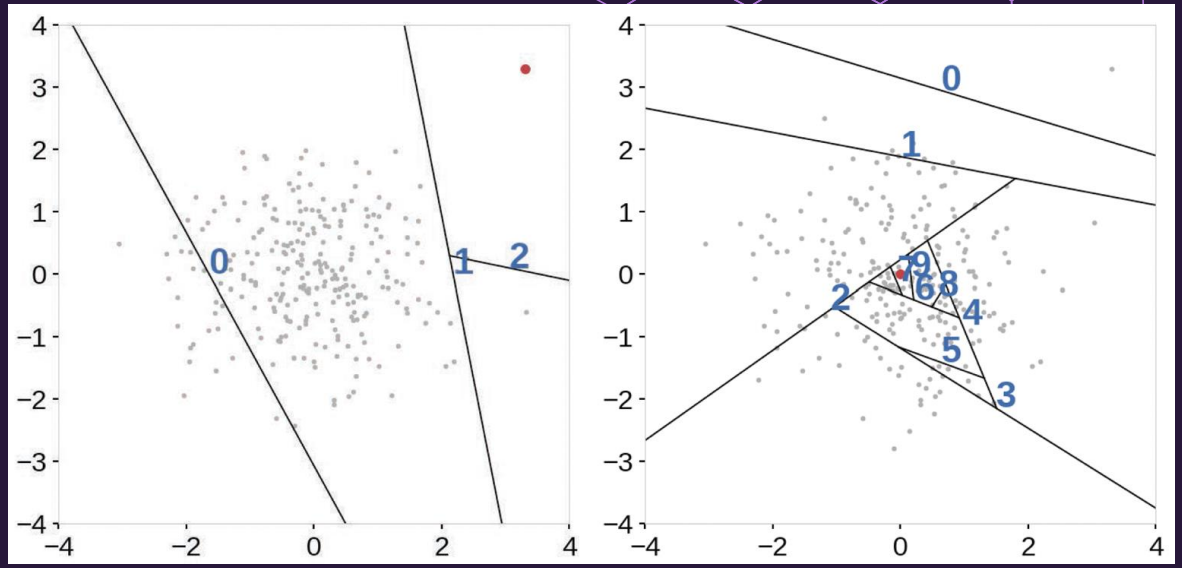
first approach:

add different class: other

Accuracy: 73%

positive: inlier
negative: outlier

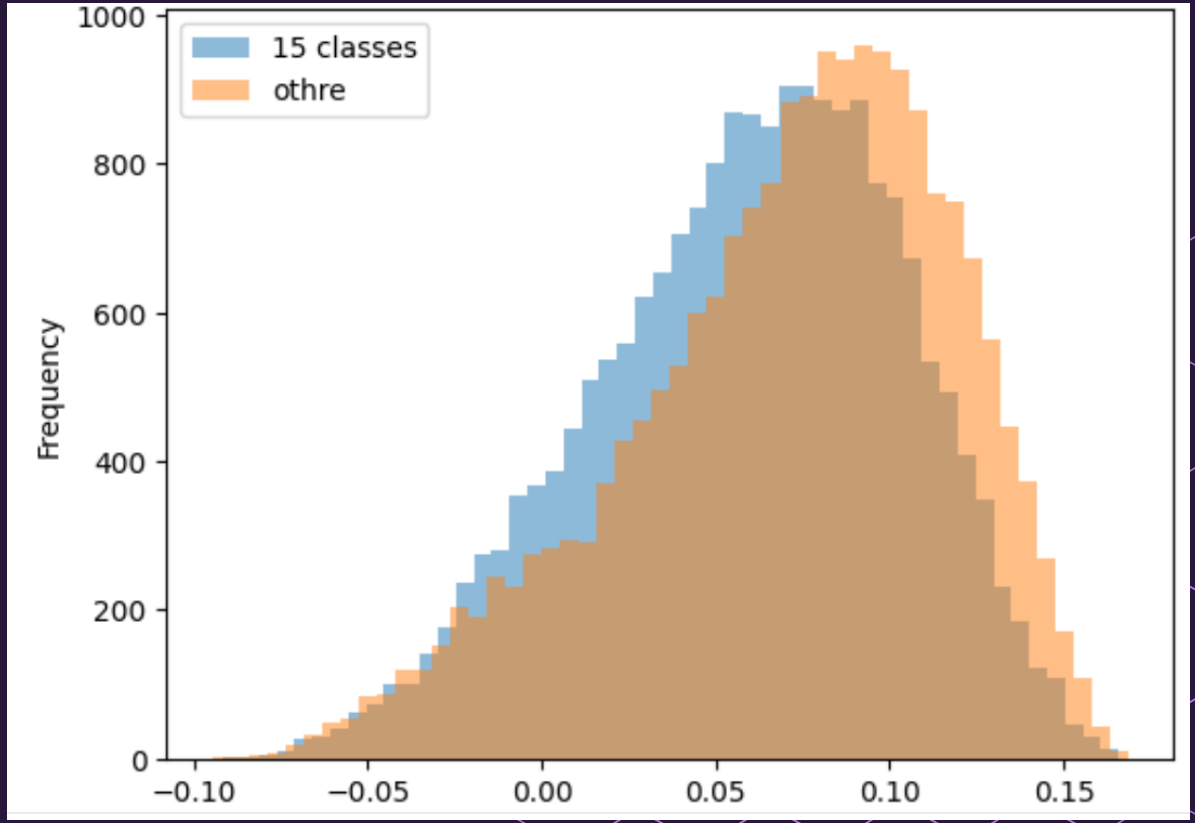
second approach: Isolation forest



- How many splits does it take for a sample point to be isolated?

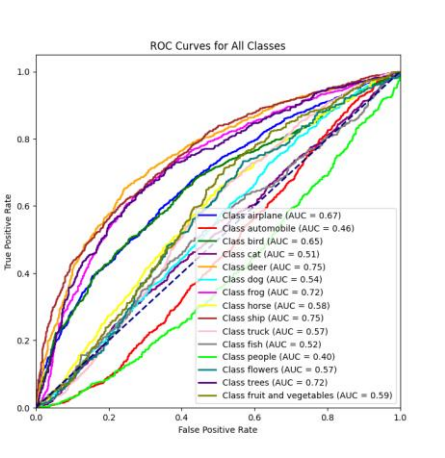
- A regular point is much harder to isolate than an anomaly point

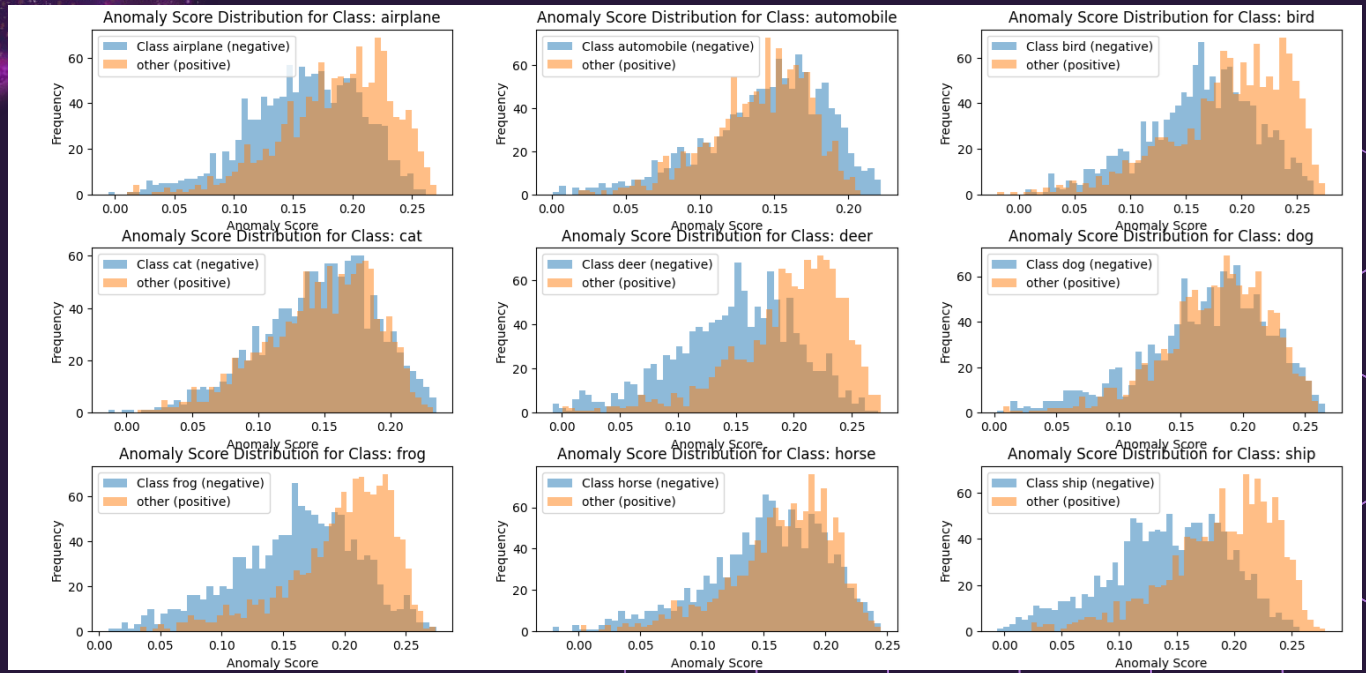
one isolation forest for all classes



positive: inlier
negative: outlier

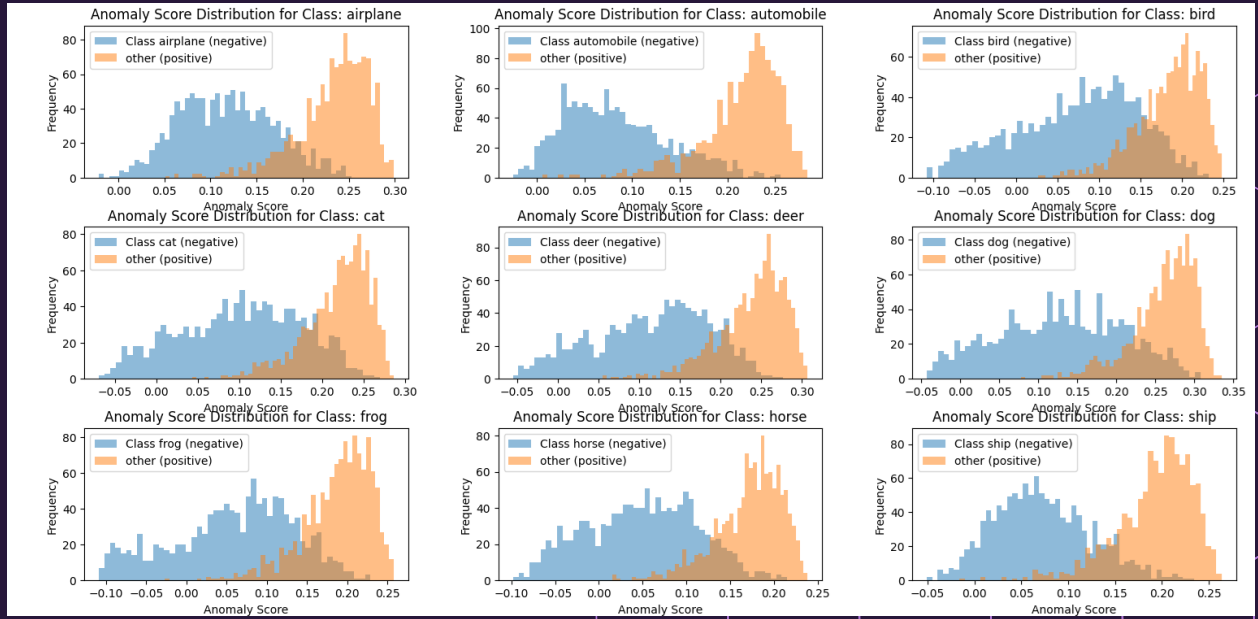
isolation forest per class, on the image



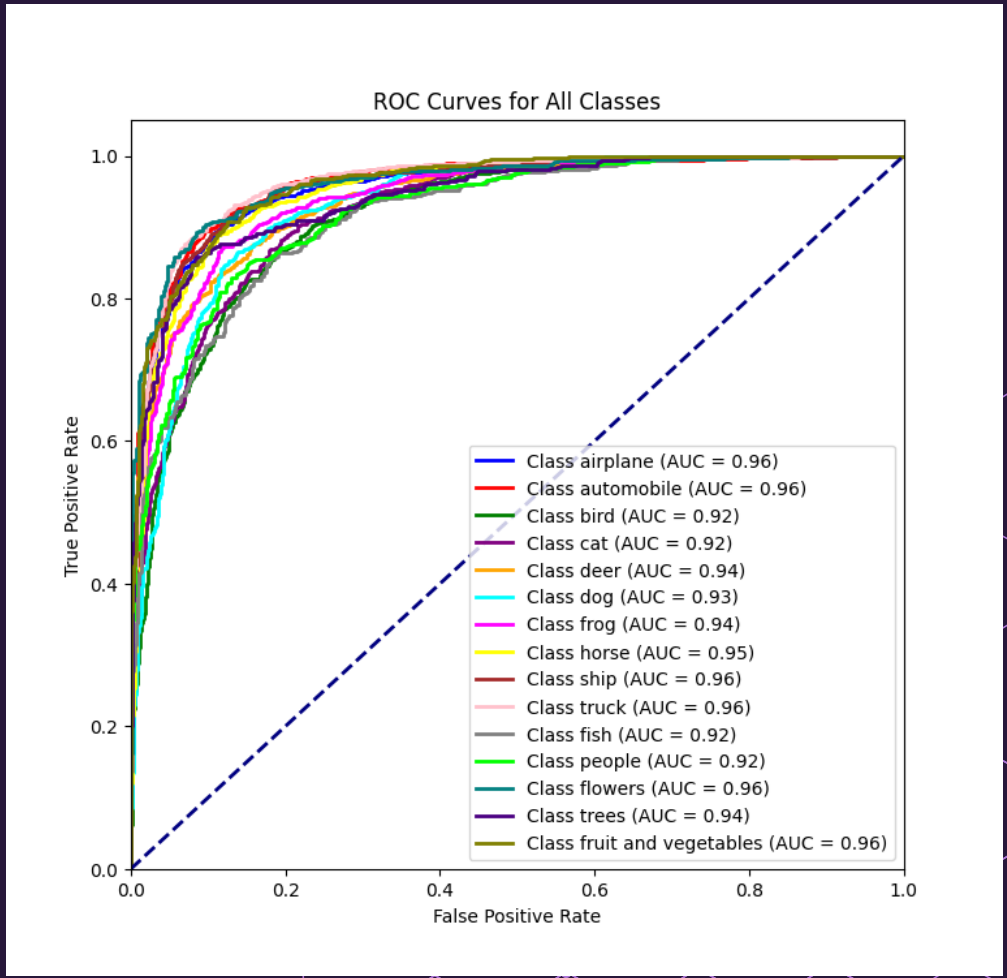


positive: inlier
negative: outlier

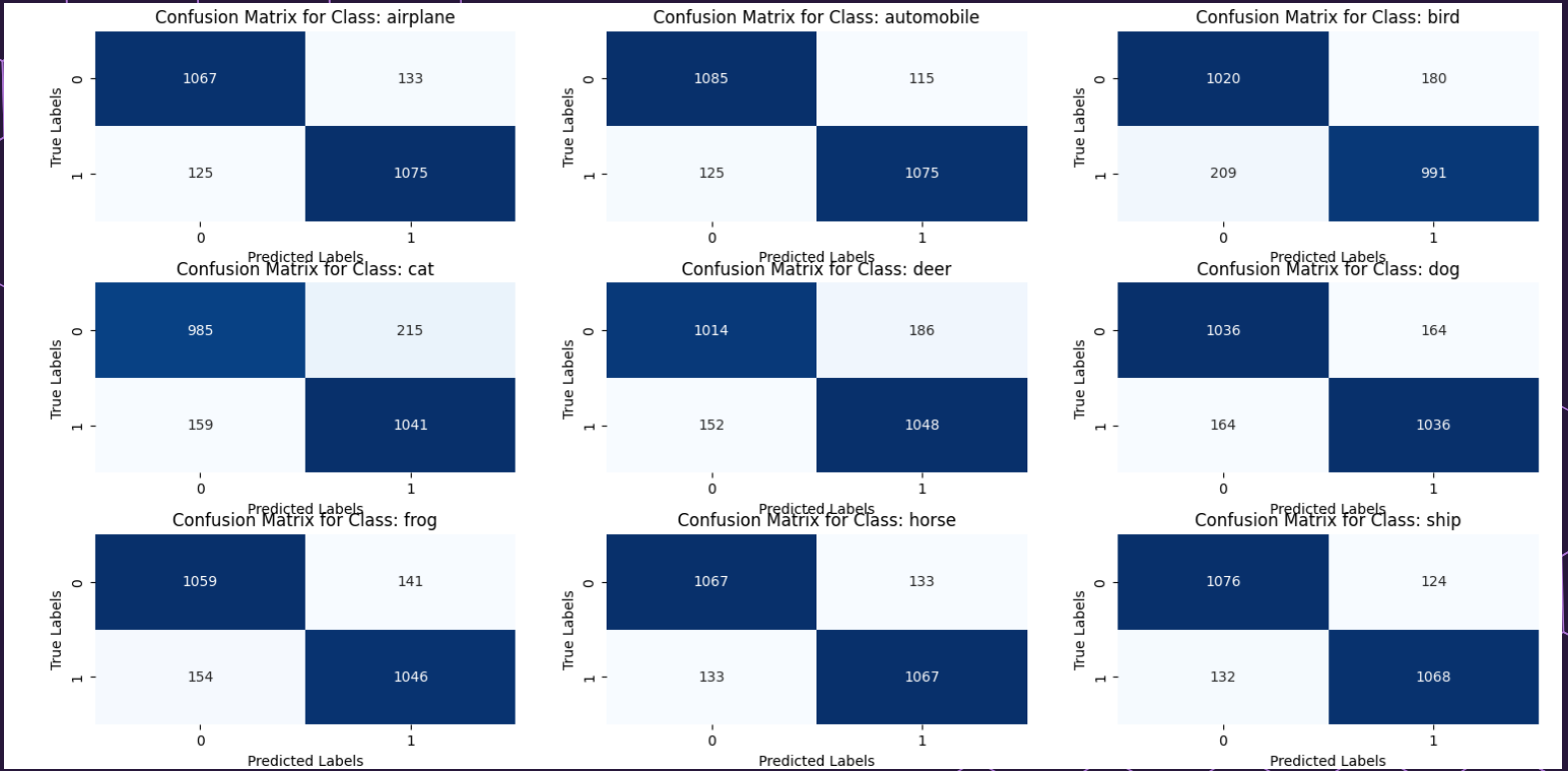
isolation forest per class, on features extracted by cnn model



positive: inlier
negative: outlier



positive: inlier
negative: outlier



positive: inlier
negative: outlier

GUI

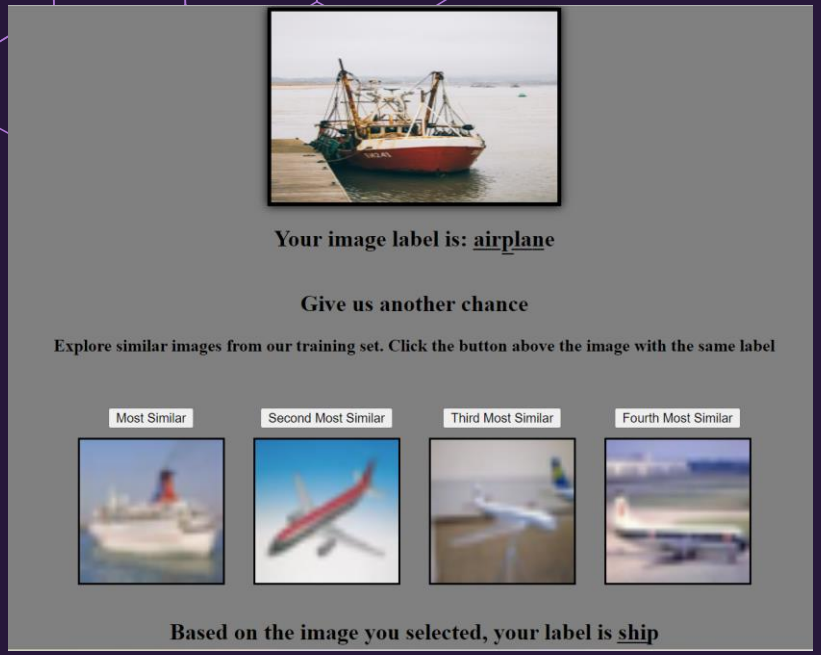
recognize anomalous label

predict a label for a image with a trained label


```
for class_idx in range(15):
  score = models[class_idx].decision_function(features_of_image)
    if score[0] > thresholds[class_idx]:
      belongs.append(class_names[class_idx])
```

```
loaded_model = CNN.load_cnn_model('../save_models/cnn_model_1.h5').model
probabilities = loaded_model.predict(image)
label = np.argmax(probabilities)
label_category = convert_to_category(label)
```

giving label based on similar image




```
def find_label_of_similar_image(image_index):
if image_index is not None:
   image_label = similar_images_label[image_index]
   label = convert_to_category(image_label)
return label
```

finding the similar images

using distance of regular features

```
for row in features_class.values:
distances.append(np.sum(np.abs(row - flattened_image)))
sorted_indices = np.argsort(distances)
four_closest_indices = sorted_indices[:4]
```

search for the similar images from potential images

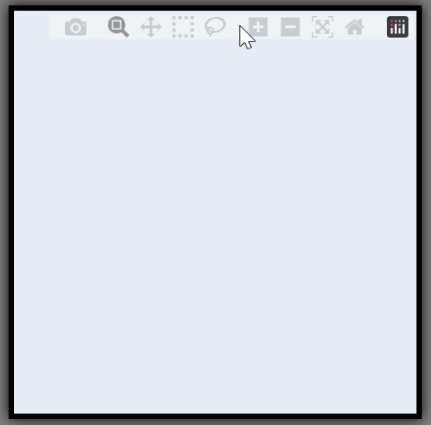
```
probabilities_indices = np.argsort(probabilities.reshape(-1))
labels = probabilities_indices[-4:]
filtered_data = sorted_data[sorted_data['label'].isin(labels)]
four_closest_vectors = filtered_data.iloc[:4, 2:]
```

using features after our model predict

```
model =
CNN.load_cnn_model('../save_models/cnn_model_1.h5').model
feat_extractor = Model(inputs=model.model.input,
outputs=loaded_model.model.get_layer('dense').output)
features = feat_extractor.predict(x_test)
```

Welcome to our Image Classifier

Upload Image

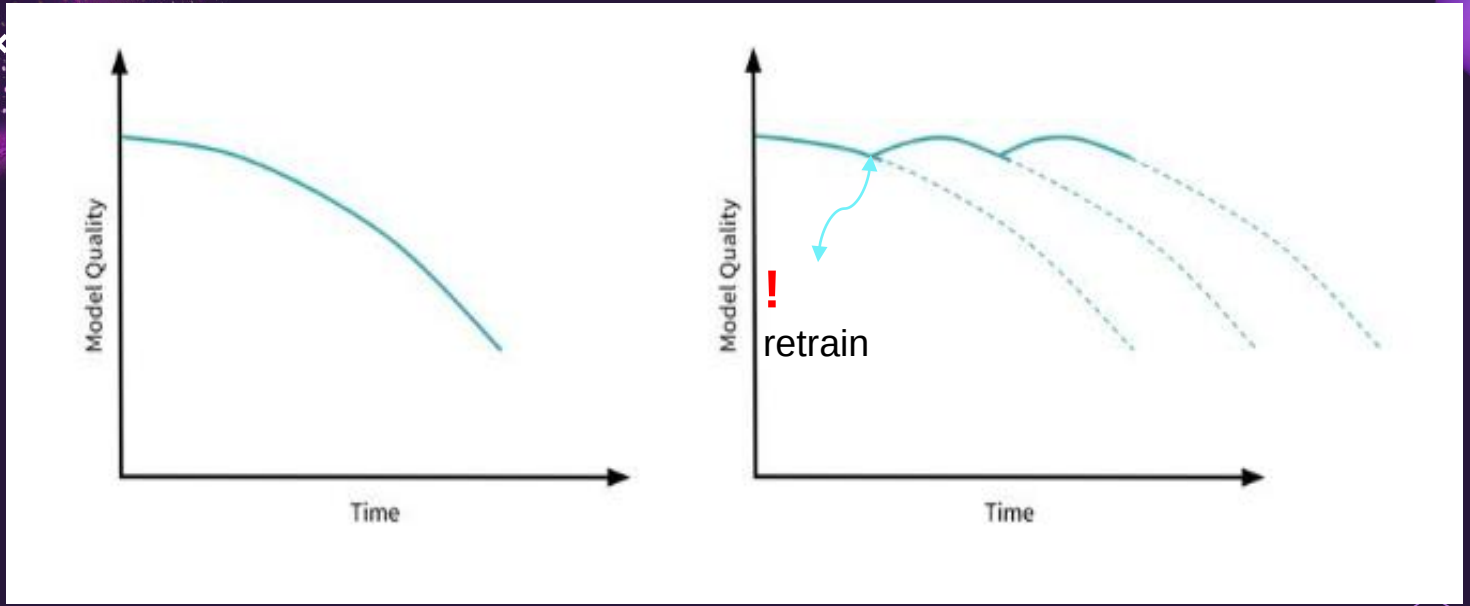


Search

Deploying & Monitoring

(NASA GROUP)

THE GOAL:



Preventing model performance decline

THE REASON:

Data drift and concept drift

Data Drift

Incoming data changes over time

Concept Drift:

Features of target variable change over time

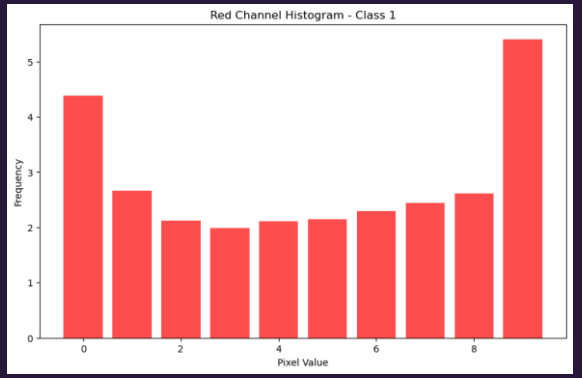
How to Detect Data Drift?

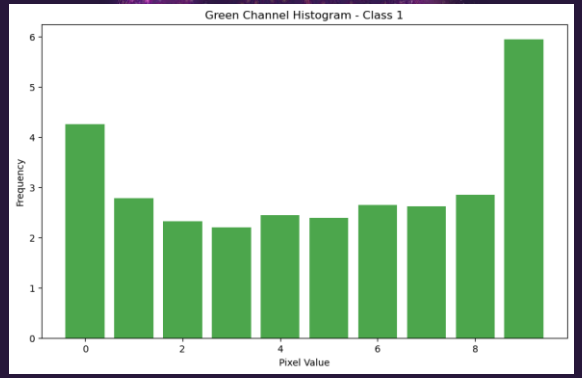
Monitoring metrics:

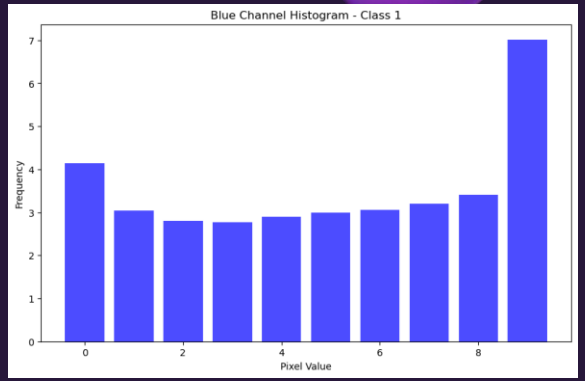
1. Distance from mean histogram of current class

2. Entropy

What is Image Histogram?

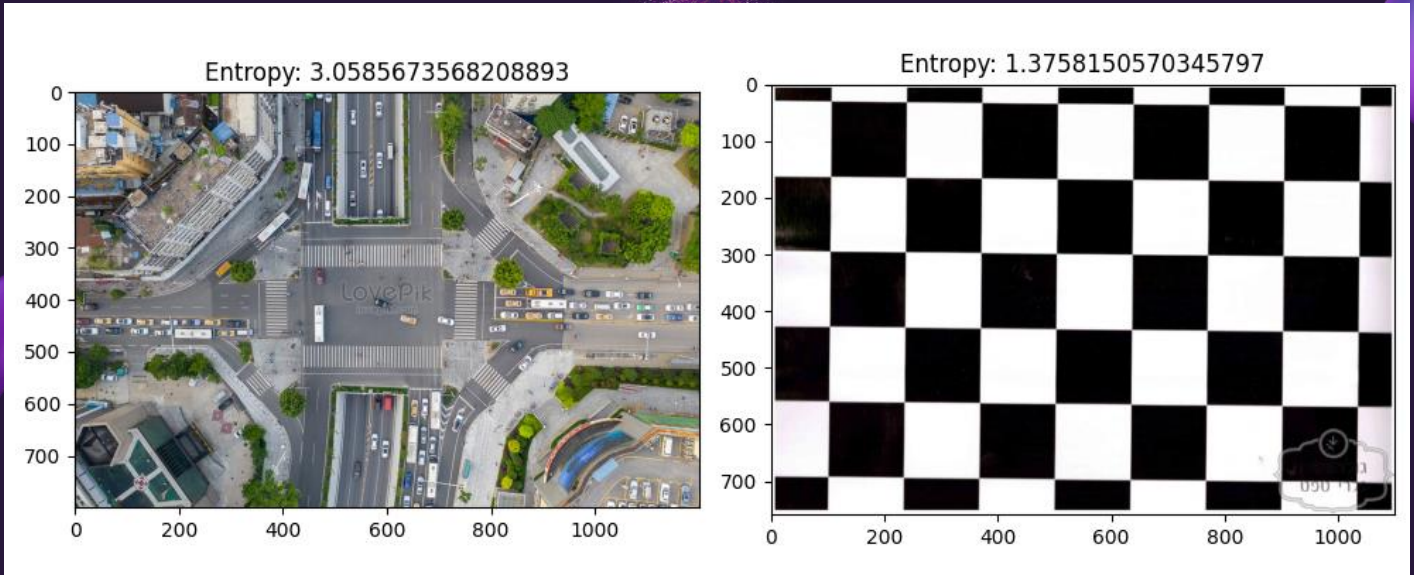






Distribution of pixels level for each color:
X-> level of color (0-255)
Y-> number of pixels in x level

What is Entropy?



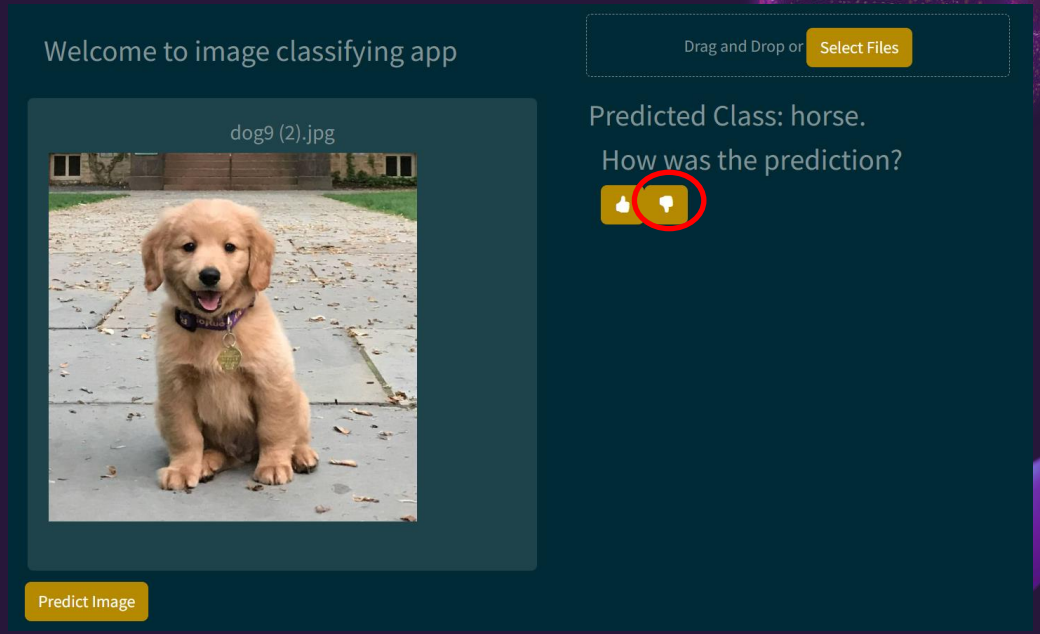
The level of randomness or uncertainty in the pixel intensity distribution of an image, reflecting its overall complexity.

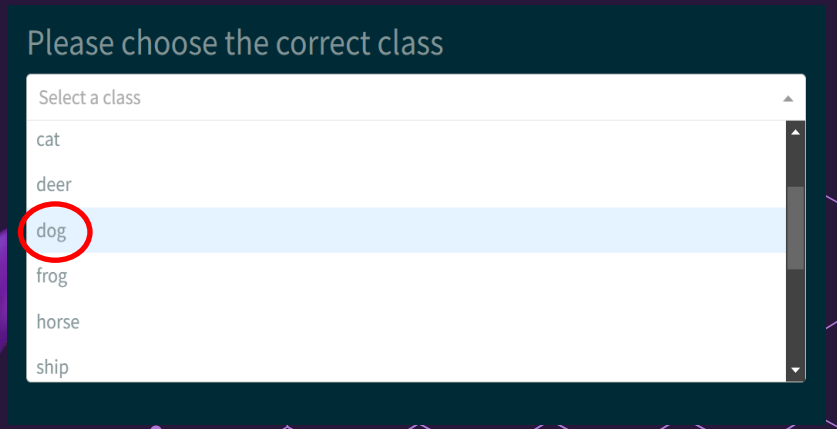
High entropy-> an image with complex patterns and visual richness.

Low entropy-> an image with simple and repetitive patterns.

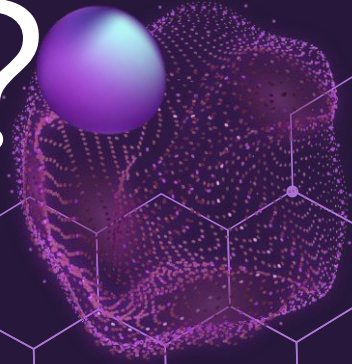
How to Detect Concept Drift?

1. Monitoring confidence in predicted class
2. Saving wrong predicted images according to user's feedback (those images are the candidates for future training)

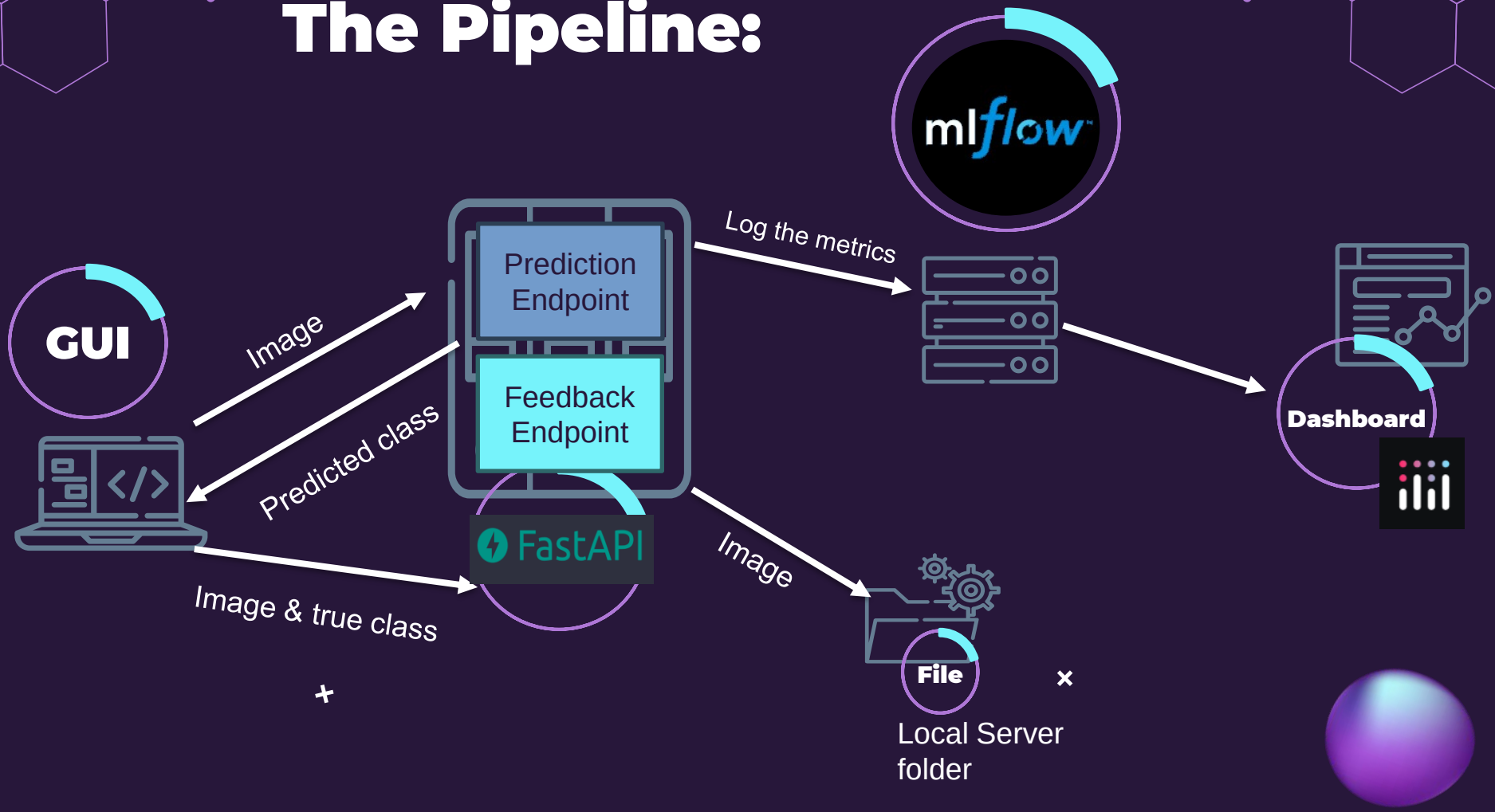




so... how did we do this?



The Pipeline:



mlflow 2.6.0

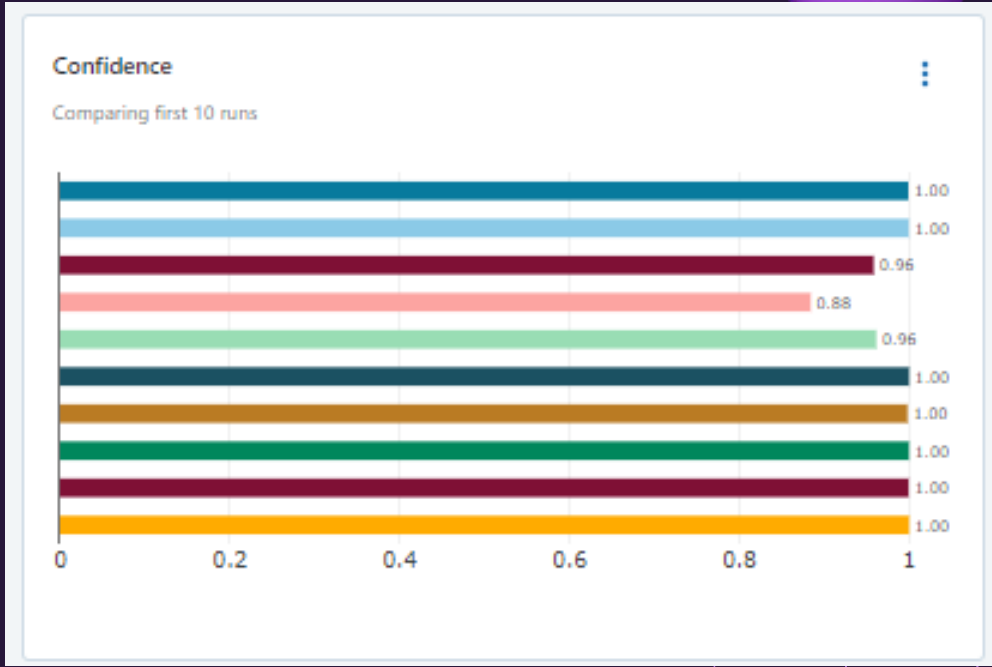
Metrics (3)

Name	Value
Confidence	0.999
Entropy	1.871
Histogram_distance	703

Tags (1)

Name	Value
class	bird

Loging metrics for each icoming image

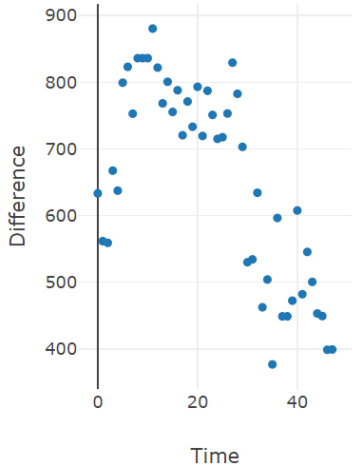


We can compare confidence of most recent 10 runs and much more!!

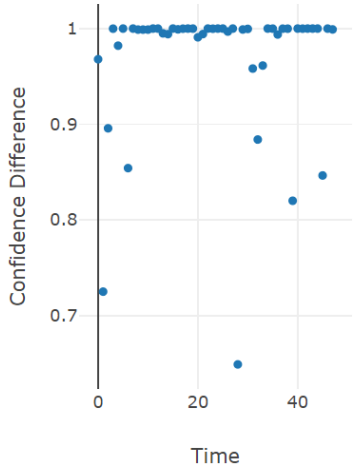
Dashboard for ML Analysis

bird

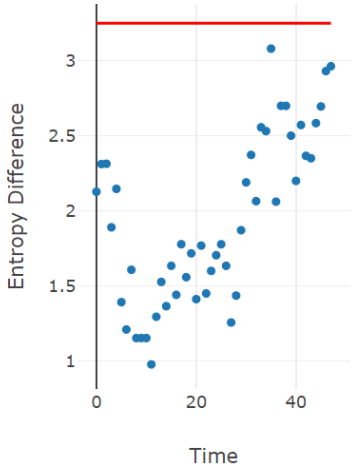
Difference from average histogram bird



Confidence Differences for bird



Entropy Differences for bird



Thank You!