Deep Learning 03: *Roadmap to using DL for your projects*

Lecture 12

Computer Vision for Geosciences

2021-06-04

Universidad Nacional Autónoma de México

So far we've used datasets which were already structured for Tensor Flow

...

$\Rightarrow$ how do we handle our own dataset?

Project: *classify volcano web-camera images*

⇒ ash plume? gas plume? no visibility? night?

⇒ I have data and a problem to solve, now what?

1. label the data
2. load the data
3. select the model
4. train and evaluate!

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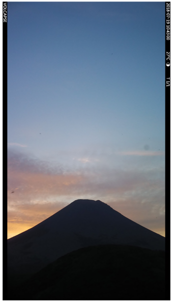
Label the data

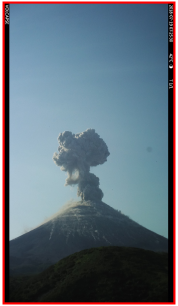
⇒ go through your dataset, and **label** images from each class

0



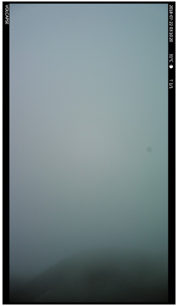
1

2

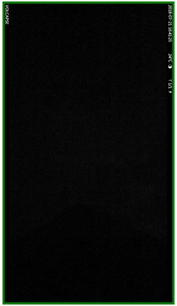


3

4



5



Label the data

$\Rightarrow$ go through your dataset, and **label** images from each class

$\Rightarrow$ search for as much **variability** possible in each class

example: variability in *class "0" = no activity*

Label the data

⇒ go through your dataset, and **label** images from each class

⇒ search for as much **variability** possible in each class

⇒ store the **file name**, **label**, and any additional information in a file (ex: .csv)

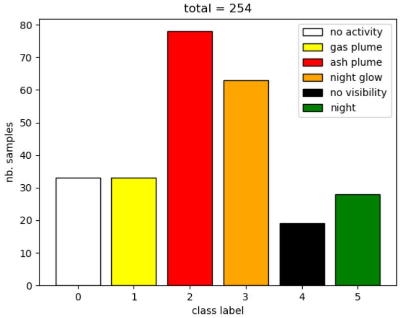
labels.csv (Editing)

```
file_name,DateTimeDigitized,label
100RECNX/RCNX0054.JPG,2018:07:18 22:02:15,1
100RECNX/RCNX0125.JPG,2018:07:18 22:08:50,2
100RECNX/RCNX0135.JPG,2018:07:18 22:09:40,2
100RECNX/RCNX0405.JPG,2018:07:18 22:32:10,1
100RECNX/RCNX2205.JPG,2018:07:19 01:02:10,2
100RECNX/RCNX3005.JPG,2018:07:19 02:08:50,2
100RECNX/RCNX3015.JPG,2018:07:19 02:09:40,2
100RECNX/RCNX3315.JPG,2018:07:19 02:34:40,2
100RECNX/RCNX4645.JPG,2018:07:19 04:25:30,0
100RECNX/RCNX5455.JPG,2018:07:19 05:33:00,0
100RECNX/RCNX5655.JPG,2018:07:19 05:49:40,1
100RECNX/RCNX5765.JPG,2018:07:19 05:58:50,0
100RECNX/RCNX6155.JPG,2018:07:19 06:31:20,1
100RECNX/RCNX6345.JPG,2018:07:19 06:47:10,0
100RECNX/RCNX6365.JPG,2018:07:19 06:48:50,2
100RECNX/RCNX6375.JPG,2018:07:19 06:49:40,2
100RECNX/RCNX6385.JPG,2018:07:19 06:50:30,2
100RECNX/RCNX6395.JPG,2018:07:19 06:51:20,2
100RECNX/RCNX6505.JPG,2018:07:19 07:00:30,2
100RECNX/RCNX6735.JPG,2018:07:19 07:19:40,0
```

NB: depending on how your data structured, you can also choose to store images in distinct folders (one for each class)

Label the data

⇒ go through your dataset, and **label** images from each class
⇒ search for as much **variability** possible in each class
⇒ store the **file name**, **label**, and any additional information in a file (ex: .csv)
⇒ check the **distribution** of your samples for each class



NB: ideally should be equally distributed, but there are ways to overcome this (class weighting)

Loading the data

⇒ use Tensor Flow's **Data API** to create and manipulate **dataset object**

⇒ **shuffle** your data, and **split** into train, validate, and test datasets

⇒ one way to do that:

```
# Load labels file
df = pd.read_csv("train.csv")

# Set indexes for train, test, validation datasets
n = len(df)
idx = np.arange(n) # Create array with n integers
np.random.seed(123) # Set seed to keep same randomization
np.random.shuffle(idx) # Modify sequence in-place by shuffling its contents

train_r, val_r, test_r = 0.8, 0.1, 0.1 # Set ratios for each dataset
idx_for_splitting = [int(n * train_r), int(n * (train_r+val_r))]
train_idx, val_idx, test_idx = np.split(idx, idx_for_splitting)

# Create tensor flow data set
file_names = df["file_name"].values
labels = df["label"].values

train_ds_raw = tf.data.Dataset.from_tensor_slices((file_names[train_idx], labels[train_idx]))
val_ds_raw = tf.data.Dataset.from_tensor_slices((file_names[val_idx], labels[val_idx]))
test_ds_raw = tf.data.Dataset.from_tensor_slices((file_names[test_idx], labels[test_idx]))
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```

Prepare the data

At this stage, the datasets generated are *TensorSliceDataset* objects, storing *filename* and *label*:

```
for file_name, label in iter(train_ds_raw):
    print('---')
    print(file_name)
    print(label)

# Returns:
# ---
# tf.Tensor(b'104RECNX/RCNX3406.JPG', shape=(), dtype=string)
# tf.Tensor(3.0, shape=(), dtype=float64)
# ---
# tf.Tensor(b'100RECNX/RCNX6795.JPG', shape=(), dtype=string)
# tf.Tensor(2.0, shape=(), dtype=float64)
# ...
```

⇒ we now need to "instruct" which operations these datasets should undergoe during training

⇒ dataset objects allow to **chain transformations** easily: *map functions, define batch, etc.*

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⇒ we now need to "instruct" which operations these datasets should undergoe during training

⇒ dataset objects allow to **chain transformations** easily: *map functions, define batch, etc.*

Prepare the data

⇒ chain transformations:

```python
resize_h, resize_w = 130, 230

def preprocess(image_file, label):

    # Read image
    image = tf.io.read_file(path_root + image_file)
    image = tf.image.decode_jpeg(image, channels=3)  # returns uint8 tensor

    # Convert to float to prepare for resize
    image = tf.image.convert_image_dtype(image, tf.float32)

    # Resize image (original size/10)
    # => returns float [0-1]
    resized_image = tf.image.resize(image,
                                    size=(resize_h, resize_w),  # (new_height, new_width)
                                    preserve_aspect_ratio=True)

    # Xception preprocess_input:
    # => input: floating point with values in range [0, 255] (doc)
    # => returns scaled input pixels between -1 and 1 (https://keras.io/api/applications/xception/)
    resized_image = tf.multiply(resized_image, 255)  # switch to range 0-255
    final_image = tf.keras.applications.xception.preprocess_input(resized_image)  # not clear how to give inputs (dtype/range)

    return final_image, label

batch_size = 32
train_ds = train_ds_raw.shuffle(buffer_size=1000, seed=None)  # => at each epoch training will see samples in different order
train_ds = train_ds_raw.map(preprocess).batch(batch_size).prefetch(1)
val_ds = val_ds_raw.map(preprocess).batch(batch_size).prefetch(1)
test_ds = test_ds_raw.map(preprocess).batch(batch_size).prefetch(1)
```

⇒ when the dataset is "consumed" during training, these operations are performed on-the-fly

Prepare the data

⇒ chain transformations:

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```

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Select the model

⇒ when you have a small amount of labeled data, choose a **transfer learning** solution

Code from last week exercise:

```
# Load Xception model and define as base model
base_model = tf.keras.applications.xception.Xception(weights="imagenet",
                                                     include_top=False,
                                                     input_shape=(resize_h, resize_w, 3))
# Freeze base layers
for layer in base_model.layers:
    layer.trainable = False

# Add layers to train classifier
avg = tf.keras.layers.GlobalAveragePooling2D()(base_model.output)  # takes base_model ouputs as input
output = tf.keras.layers.Dense(n_classes, activation="softmax")(avg)  # takes GlobalAveragePooling2D layer as input

# Create final model
model = tf.keras.Model(inputs=base_model.input, outputs=output)

# Compile
optimizer = tf.keras.optimizers.Adam(learning_rate=0.1)
model.compile(loss="sparse_categorical_crossentropy", optimizer=optimizer, metrics=["accuracy"])
```

NB: for simplicity we do not specify the fine-tuning steps here

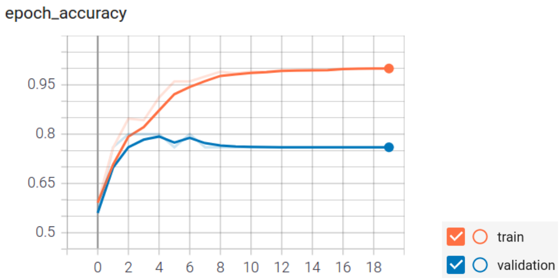
Train

Recall our dataset does not have a *uniform class distribution*
⇒ we can compensate for that using the `class_weight` option:

```
# Calculate class weights
labels_int = labels.astype('int64')
class0_nb, class1_nb, class2_nb, class3_nb, class4_nb, class5_nb = np.bincount(labels_int)
scaling_factor = n_samples / n_classes
class_weight = {0: (1 / class0_nb) * scaling_factor,
                1: (1 / class1_nb) * scaling_factor,
                2: (1 / class2_nb) * scaling_factor,
                3: (1 / class3_nb) * scaling_factor,
                4: (1 / class4_nb) * scaling_factor,
                5: (1 / class5_nb) * scaling_factor
                }
# Train
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir, histogram_freq=1, update_freq='batch')
history = model.fit(train_ds,
                    epochs=epochs,
                    validation_data=val_ds,
                    callbacks=[tensorboard_callback],
                    class_weight=class_weight)
```

Train

⇒ track accuracy of *training* & *validation* datasets with TensorBoard:



NB: there's room for improvement! e.g., more training data, data augmentation, regularization, fine-tuning, etc.

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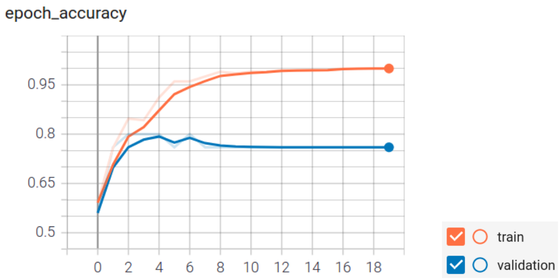

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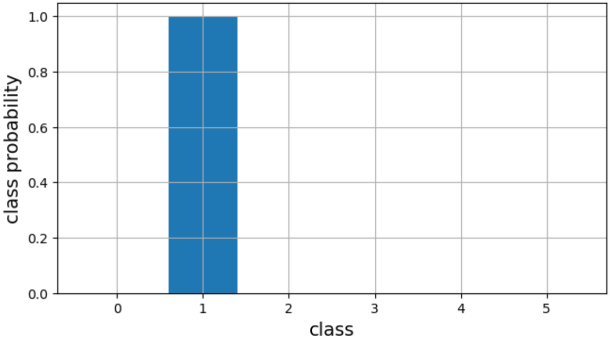
Predict

⇒ how well is our model predicting the test dataset?



class 1 = gas plume

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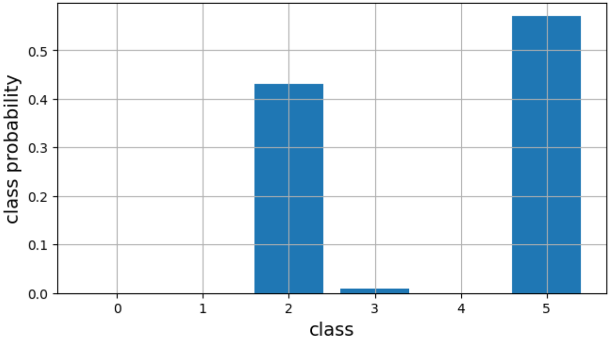
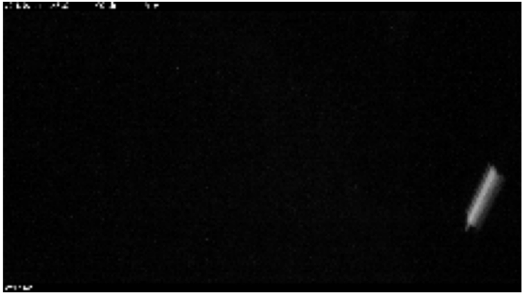


class 5 = night



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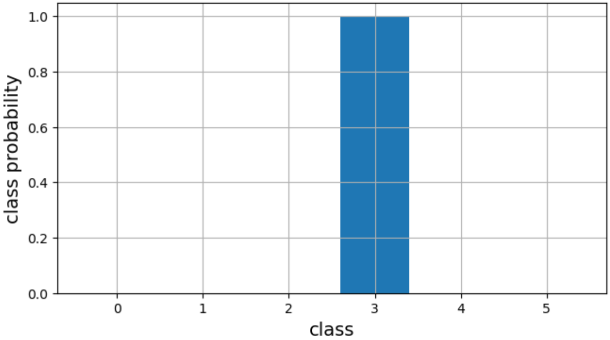
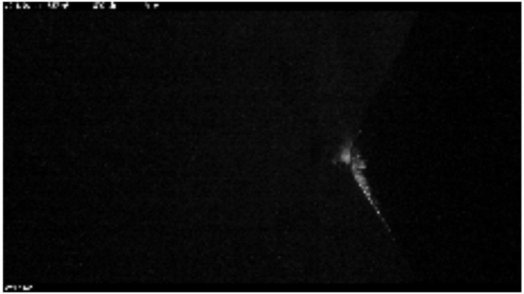


class 3 = night glow



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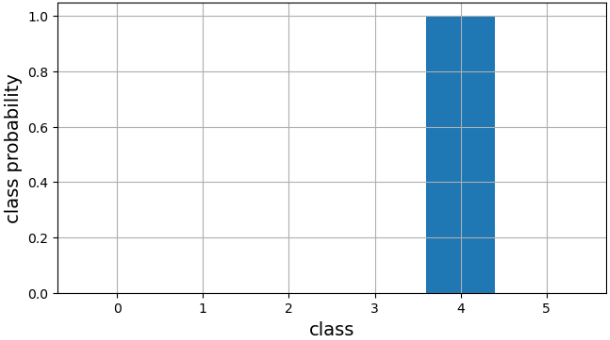
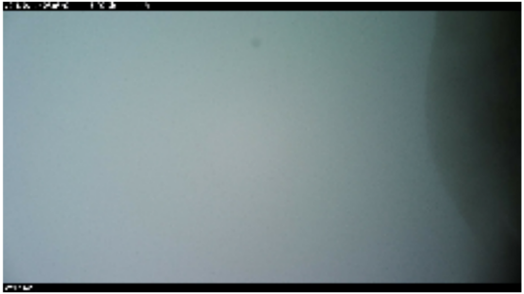


class 4 = no visibility



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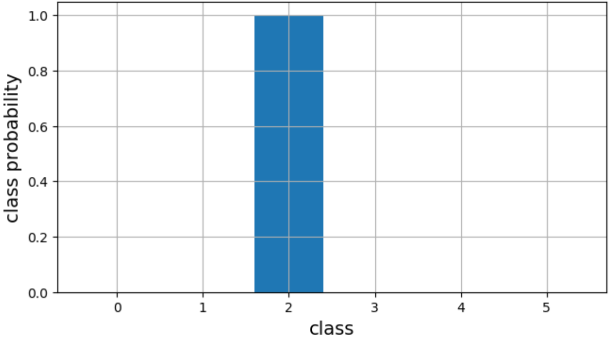

class 2 = ash plume

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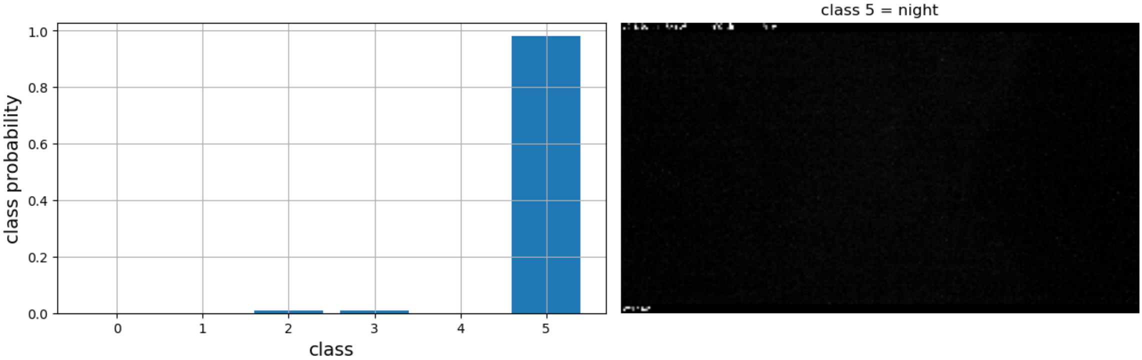

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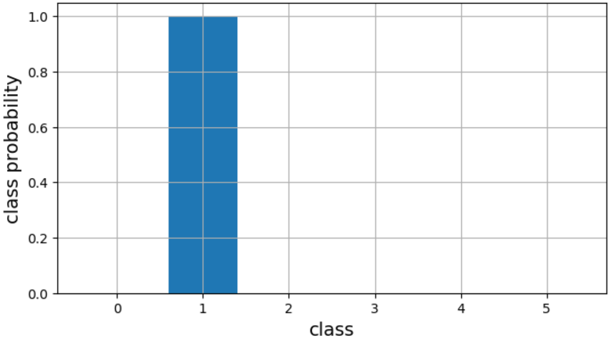

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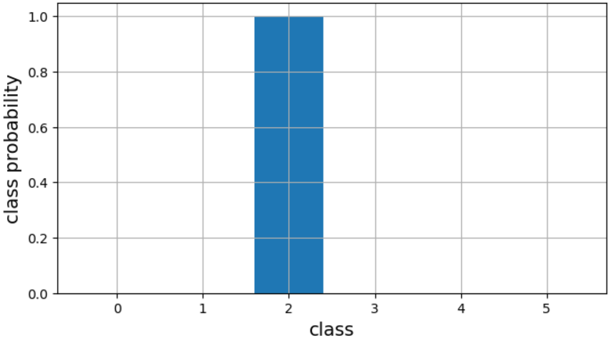

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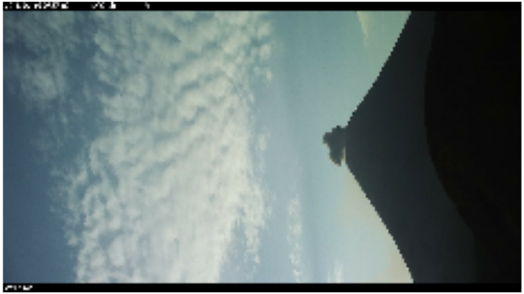

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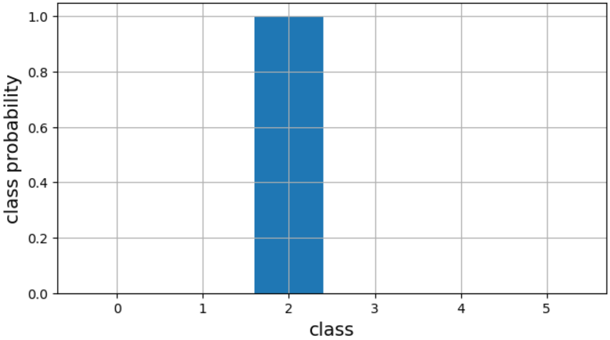

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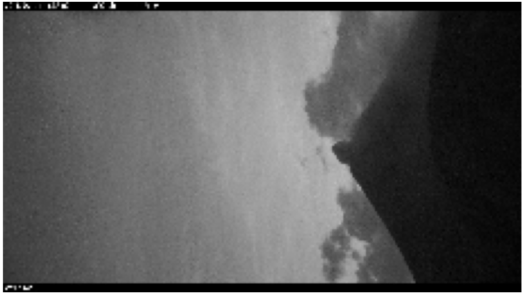

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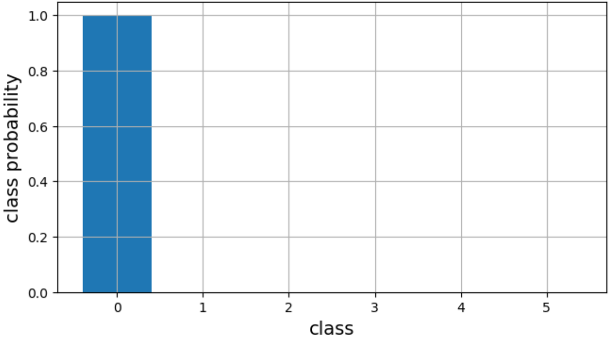
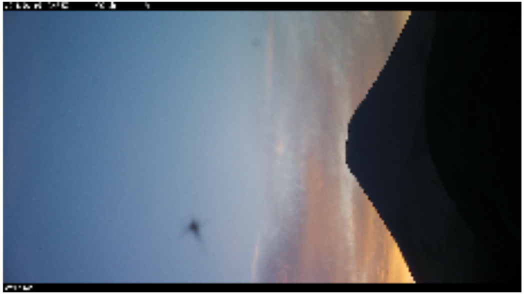


class 0 = no activity



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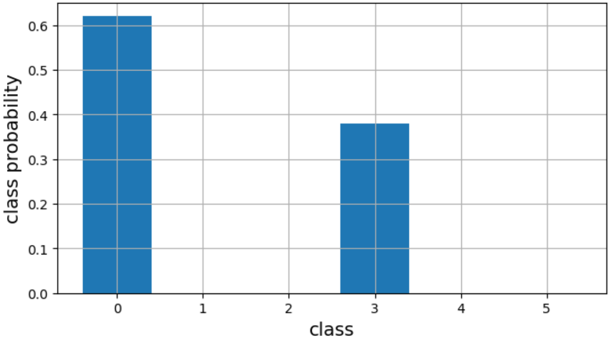

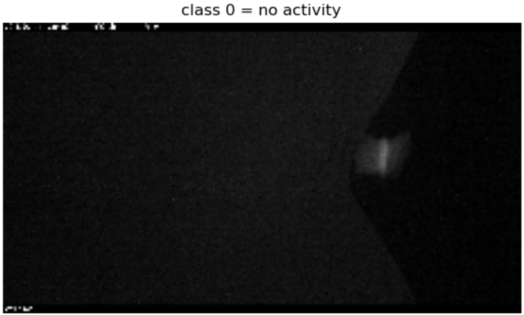

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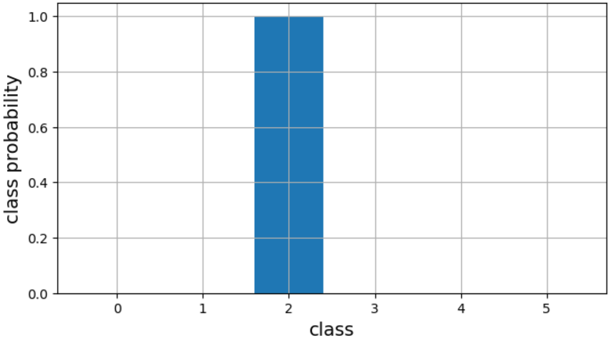

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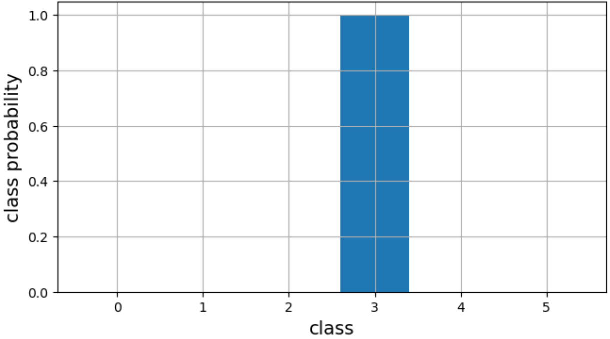

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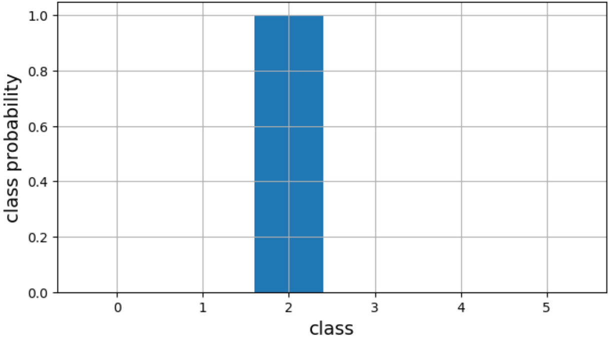
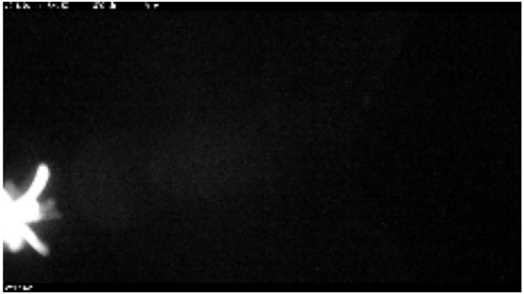
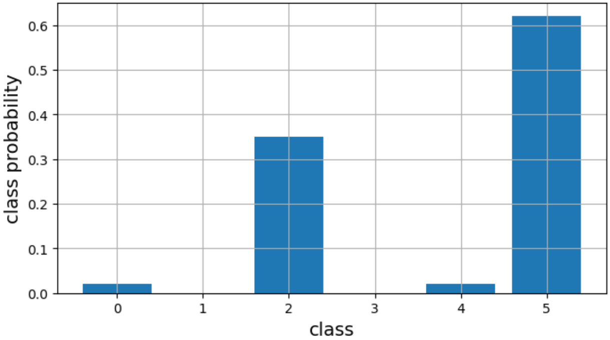


class 2 = ash plume



Predict

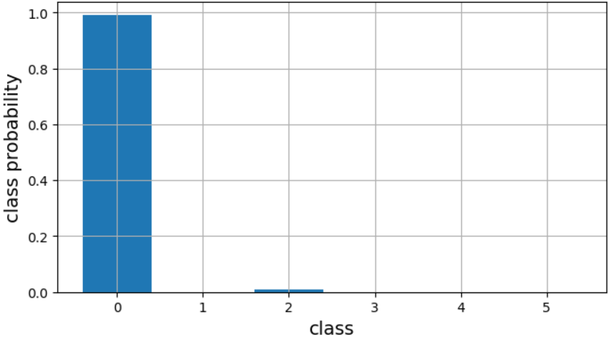
⇒ how well is our model predicting the test dataset?



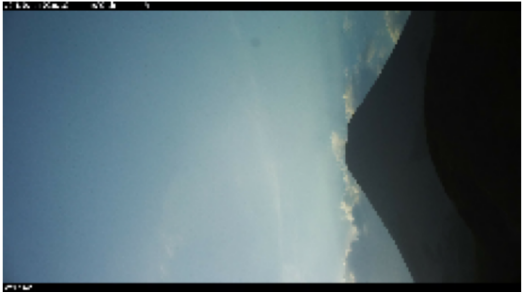
class 5 = night

Predict

⇒ how well is our model predicting the test dataset?

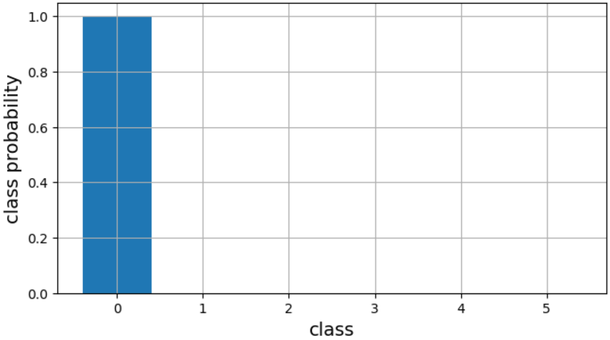


class 0 = no activity



Predict

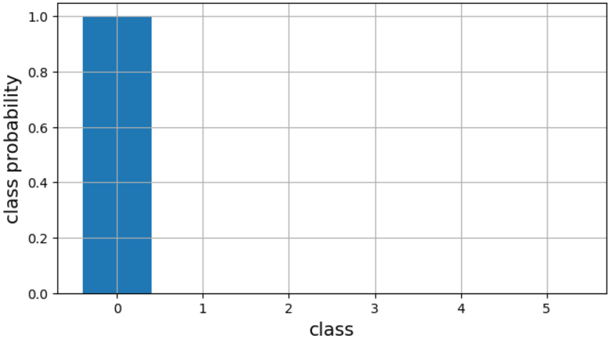
⇒ how well is our model predicting the test dataset?



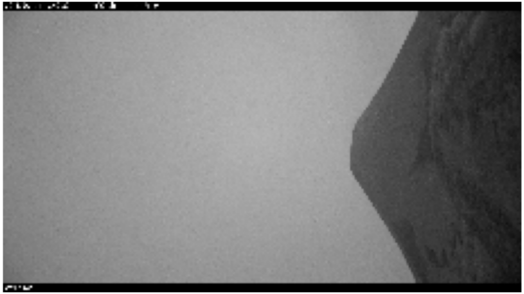
class 0 = no activity

Predict

⇒ how well is our model predicting the test dataset?

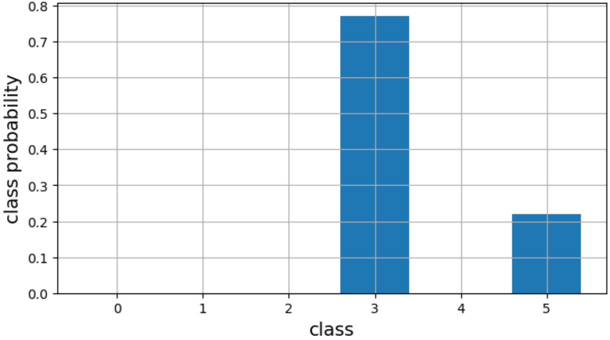


class 0 = no activity



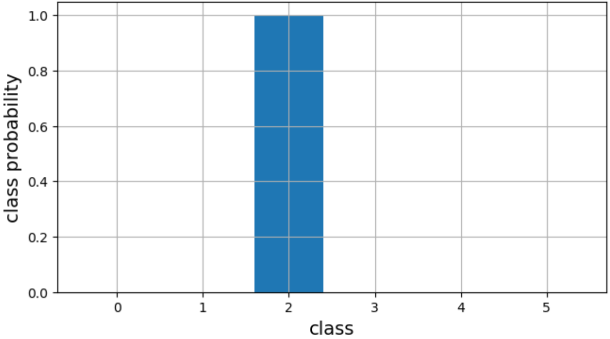
Predict

⇒ how well is our model predicting the test dataset?



Predict

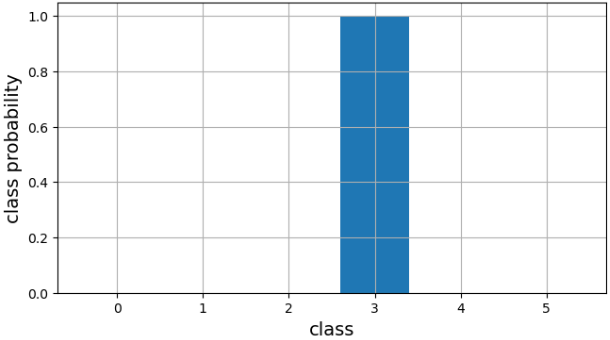
⇒ how well is our model predicting the test dataset?



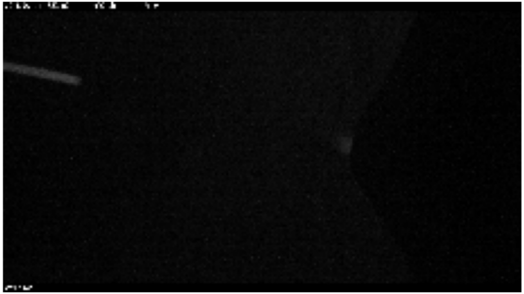
class 2 = ash plume

Predict

$\Rightarrow$ how well is our model predicting the test dataset?

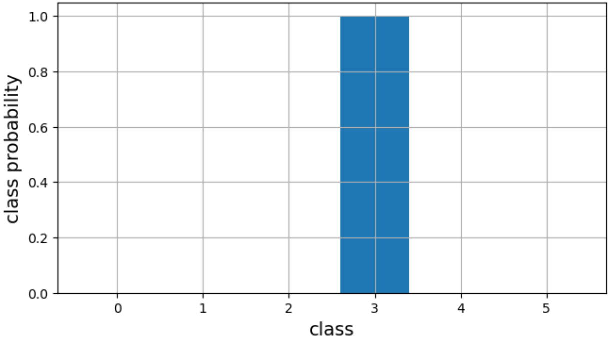


class 3 = night glow



Predict

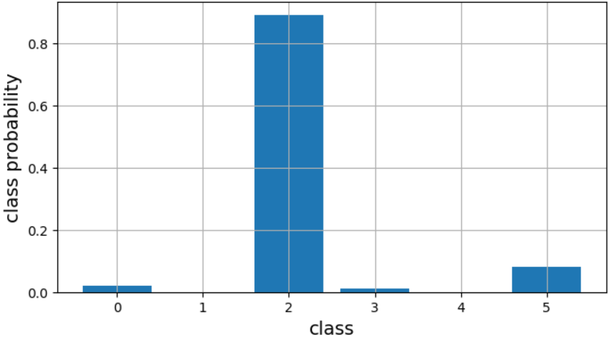
$\Rightarrow$ how well is our model predicting the test dataset?



class 3 = night glow

Predict

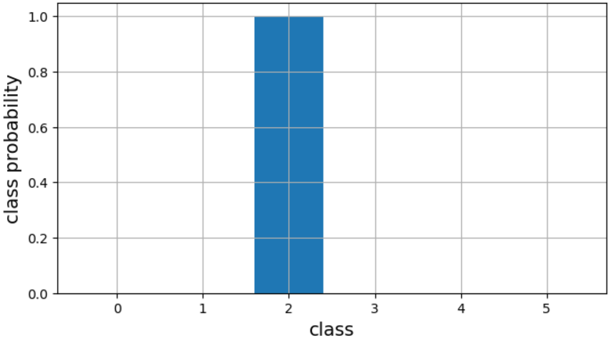
⇒ how well is our model predicting the test dataset?



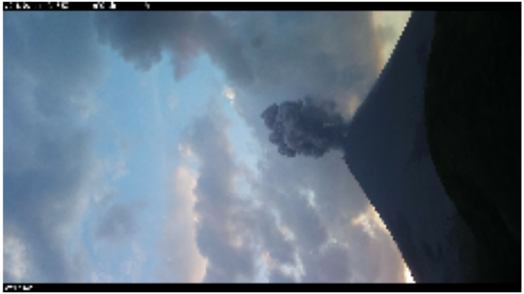
class 2 = ash plume

Predict

$\Rightarrow$ how well is our model predicting the test dataset?

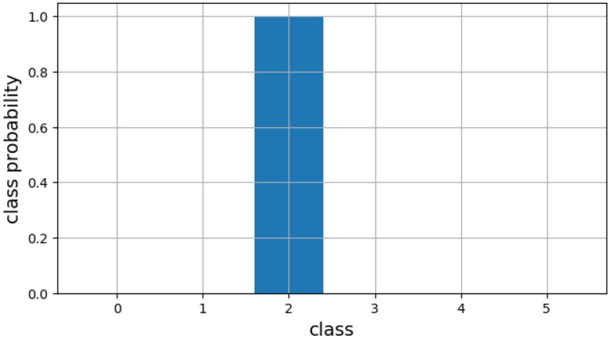


class 2 = ash plume



Predict

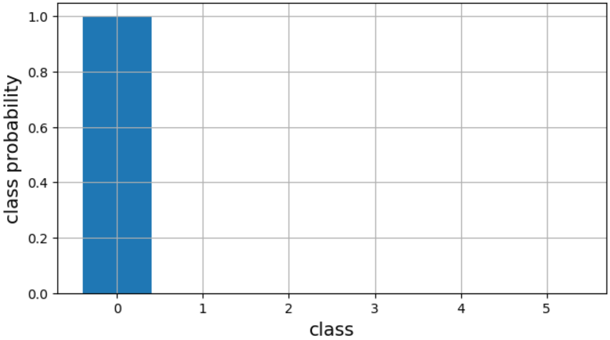
$\Rightarrow$ how well is our model predicting the test dataset?



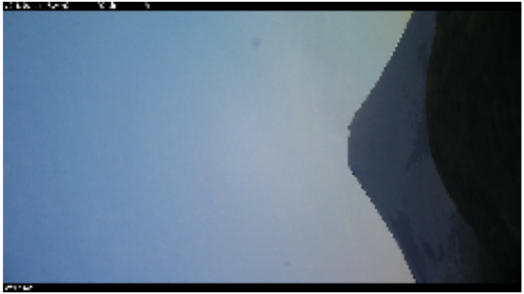
class 2 = ash plume

Predict

⇒ how well is our model predicting the test dataset?



class 0 = no activity



⇒ not bad for such little training dataset and time to train the model

⇒ but need to increase the number & diversity of the training images to avoid overfitting!

$\Rightarrow$ not bad for such little training dataset and time to train the model

$\Rightarrow$ but need to increase the number & diversity of the training images to avoid overfitting!

THE END

(or rather the begining ?)