```
import tensorflow as tf
import tensorflow_datasets as tfds
import matplotlib.pyplot as plt
!pip install -q tfds-nightly matplotlib
\rightarrow
                                               - 5.3/5.3 MB 35.1 MB/s eta 0:00:00
dataset, info = tfds.load('smallnorb', with_info=True, as_supervised=True) # Dataset take from https://www.tensorflow.org/datasets/catal
# as_supervised=True secures the model.fit receives tuples
# with_info=True to get metadata
# is loading like a dict, no tuples dataset['train'] would return {'image': <Tensor>, 'label': <int>}
Example 1.00 warning:absl:Variant folder /root/tensorflow_datasets/smallnorb/2.0.0 has no dataset_info.json
     Downloading and preparing dataset Unknown size (download: Unknown size, generated: Unknown size, total: Unknown size) to /root/tenso
     DI Completed...: 100%
                            6/6 [00:30<00:00, 3.66s/ url]
                       249/249 [00:30<00:00, 14.79 MiB/s]
     DI Size...: 100%
     Extraction completed...: 100%
                                  6/6 [00:30<00:00. 5.08s/ file]
     Dataset smallnorb downloaded and prepared to /root/tensorflow_datasets/smallnorb/2.0.0. Subsequent calls will reuse this data.
# Visualize some examples from the train data
# select the test data
test_data = dataset['test']
# Create 2x2 subplot grid
plt.figure(figsize=(8, 8))
# Plot 5 examples, one of each category
selected = {}
for image, label in test_data:
    label_val = int(label.numpy())
    if label val not in selected:
        selected[label_val] = image
    # Stop when we have all 5 labels
    if len(selected) == 5:
       break
# Plot them
plt.figure(figsize=(10, 2))
for i, (label_val, image) in enumerate(sorted(selected.items())):
    plt.subplot(1, 5, i + 1)
    plt.imshow(image.numpy().squeeze(), cmap='gray')
    plt.title(f'Label: {label_val}')
    plt.axis('off')
plt.show()
plt.tight_layout()
plt.show()
→ <Figure size 800x800 with 0 Axes>
                                                                                                Label: 4
           Label: 0
                                Label: 1
                                                      Label: 2
                                                                           Label: 3
     <Figure size 640x480 with 0 Axes>
# General info
print("Total examples:", info.splits['train'].num_examples + info.splits['test'].num_examples,
      "Training set:", info.splits['train'].num_examples,
      "Test set:", info.splits['test'].num_examples)
print(image.dtype, tf.reduce_max(image), tf.reduce_min(image))# Normalizar soon
test data = dataset['test']
Total examples: 48600 Training set: 24300 Test set: 24300
     <dtype: 'uint8'> tf.Tensor(228, shape=(), dtype=uint8) tf.Tensor(81, shape=(), dtype=uint8)
```

```
# Extract the tuples (image, labels) for the train and test sets
for example in test_data.take(1):
    print(example) # it yields a tuple, an image tensor normalized and a label is a scalar int 64
→ (<tf.Tensor: shape=(96, 96, 1), dtype=uint8, numpy=</pre>
     array([[[206],
              [206],
              [206],
              [206],
              [206],
             [206]],
             [[206],
              [206],
              [206],
              [206],
              [206],
              [206]],
             [[206],
              [206],
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              [206],
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              [205],
              [205],
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             [206]],
             [[205],
              [205],
              [205],
              [205],
              [206],
             [206]],
             [[206],
              [206],
              [206],
              [206],
              [206]]], dtype=uint8)>, <tf.Tensor: shape=(), dtype=int64, numpy=3>)
def normalize(image, label):
    image = tf.cast(image, tf.float32) / 255.0
    return image, label
# Only normalize test_data
test_data = test_data.map(normalize)
for example in test_data.take(1):
    print(example)
(<tf.Tensor: shape=(96, 96, 1), dtype=float32, numpy=
array([[[0.80784315],
              [0.80784315],
              [0.80784315],
              [0.80784315],
              [0.80784315],
              [0.80784315]],
             [[0.80784315],
              [0.80784315],
              [0.80784315],
              [0.80784315],
              [0.80784315],
              [0.80784315]],
             [[0.80784315],
              [0.80784315],
              [0.80784315],
              [0.80784315],
```

```
[0.80784315]
             [0.80784315]],
            [[0.8039216],
             [0.8039216],
             [0.8039216],
             [0.8039216],
             [0.80784315],
             [0.80784315]],
            [[0.8039216],
             [0.8039216],
             [0.8039216],
             [0.8039216],
             [0.80784315],
             [0.80784315]],
            [[0.80784315],
             [0.80784315],
             [0.80784315],
             [0.80784315],
             [0.80784315],
             [0.80784315]]], dtype=float32)>, <tf.Tensor: shape=(), dtype=int64, numpy=3>)
# Use only the test set and separate it 80% train set (x train), 20% test set (x test)
split_size = int(24300 * 0.8) # 19440
x_train = test_data.take(split_size)
x_test = test_data.skip(split_size)# skip function, it means you're ignoring a certain number of elements from the beginning of the datas
print( "Final examples in the train set:", len(x_train),
      "final examples in the test set:", len(x_test))
Final examples in the train set: 19440 final examples in the test set: 4860
for _, label in x_train.take(1):
   print(label.shape) # should be () not (5,)
→ ()
# Create the model
# Set random seed
tf.random.set_seed(29)
# Create the model
model = tf.keras.Sequential([
   tf.keras.layers.Flatten(input_shape=(96, 96, 1)),
   tf.keras.layers.Dense(128, activation="relu"),
   tf.keras.layers.Dropout(0.3), # 30% of neurons dropped during training
   tf.keras.layers.Dense(64, activation="relu"),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(5, activation="softmax")
])
# Compile the model
model.compile(loss=tf.keras.losses.SparseCategoricalCrossentropy(),
                optimizer=tf.keras.optimizers.Adam(learning_rate=1e-4),
                metrics=["accuracy"])
# Fit the mode, feed it with the tuples and set up the batch
norm_history = model.fit(x_train.batch(64),
                        epochs=50,
                        validation_data= x_test.batch(64))
```

**₹** 

```
Epoch 25/50
         304/304
                                                          - 10s 32ms/step - accuracy: 0.5000 - loss: 1.0478 - val accuracy: 0.6815 - val loss: 0.8567
         Epoch 26/50
         304/304
                                                         - 8s 27ms/step - accuracy: 0.5106 - loss: 1.0426 - val_accuracy: 0.6605 - val_loss: 0.8562
         Epoch 27/50
         304/304
                                                         - 9s 29ms/step - accuracy: 0.5068 - loss: 1.0512 - val_accuracy: 0.6693 - val_loss: 0.8562
         Epoch 28/50
         304/304
                                                         - 9s 29ms/step - accuracy: 0.5199 - loss: 1.0350 - val_accuracy: 0.6741 - val_loss: 0.8215
         Epoch 29/50
                                                         - 8s 25ms/step - accuracy: 0.5171 - loss: 1.0402 - val_accuracy: 0.6815 - val_loss: 0.8233
         304/304
         Epoch 30/50
                                                          - 9s 28ms/step - accuracy: 0.5237 - loss: 1.0270 - val_accuracy: 0.7060 - val_loss: 0.7965
         304/304
         Epoch 31/50
         304/304
                                                          - 9s 29ms/step - accuracy: 0.5283 - loss: 1.0171 - val_accuracy: 0.7039 - val_loss: 0.8111
         Epoch 32/50
                                                          - 9s 29ms/step - accuracy: 0.5323 - loss: 1.0102 - val_accuracy: 0.6864 - val_loss: 0.8508
         304/304
         Epoch 33/50
         304/304
                                                          - 11s 30ms/step - accuracy: 0.5307 - loss: 1.0114 - val_accuracy: 0.6897 - val_loss: 0.8334
         Epoch 34/50
         304/304
                                                         - 9s 29ms/step - accuracy: 0.5361 - loss: 1.0022 - val_accuracy: 0.7004 - val_loss: 0.7728
         Epoch 35/50
                                                          - 9s 28ms/step - accuracy: 0.5311 - loss: 1.0116 - val_accuracy: 0.6893 - val_loss: 0.8567
         304/304
         Epoch 36/50
         304/304
                                                          - 8s 26ms/step - accuracy: 0.5327 - loss: 1.0018 - val_accuracy: 0.6936 - val_loss: 0.8196
         Epoch 37/50
         304/304
                                                         – 10s 34ms/step - accuracy: 0.5468 - loss: 0.9936 - val_accuracy: 0.6973 - val_loss: 0.7898
         Epoch 38/50
                                                         - 10s 32ms/step - accuracy: 0.5390 - loss: 1.0012 - val_accuracy: 0.6829 - val_loss: 0.7866
         304/304
         Epoch 39/50
         304/304
                                                         - 9s 31ms/step - accuracy: 0.5334 - loss: 0.9998 - val_accuracy: 0.7175 - val_loss: 0.7670
         Epoch 40/50
                                                         - 9s 27ms/step - accuracy: 0.5427 - loss: 0.9905 - val_accuracy: 0.7070 - val_loss: 0.7621
         304/304 -
         Epoch 41/50
                                                         - 9s 29ms/step - accuracy: 0.5402 - loss: 0.9885 - val_accuracy: 0.6928 - val_loss: 0.7847
         304/304
         Epoch 42/50
         304/304
                                                         - 9s 29ms/step - accuracy: 0.5441 - loss: 0.9902 - val_accuracy: 0.6969 - val_loss: 0.7982
         Epoch 43/50
         304/304
                                                          - 8s 26ms/step - accuracy: 0.5497 - loss: 0.9884 - val_accuracy: 0.6922 - val_loss: 0.8278
         Epoch 44/50
         304/304 -
                                                         - 9s 30ms/step - accuracy: 0.5415 - loss: 0.9864 - val accuracy: 0.6984 - val loss: 0.7632
         Fnoch 15/50
loss_train, accur_train = model.evaluate(x_train.batch(64).prefetch(tf.data.AUTOTUNE))
loss\_test, \ accur\_test = model.evaluate(x\_test.batch(64).prefetch(tf.data.AUTOTUNE)) \# \ creating \ a \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ buffer \ and \ using \ to \ prepare \ the \ next \ the \ next
```

**- 9s** 29ms/step - accuracy: 0.5105 - loss: 1.0518 - val\_accuracy: 0.6743 - val\_loss: 0.8527

```
# Evaluate the model on the test
```

# the GPU is still busy with the current

```
print(f'Final accuracy training:{100*accur_train:.2f}%, final loss training {loss_train}')
print(f'Final accuracy test:{100*accur_test:.2f}%, final loss test {loss_test}')
```

304/304 **- 4s** 11ms/step - accuracy: 0.7117 - loss: 0.7625 76/76 - **2s** 8ms/step - accuracy: 0.7093 - loss: 0.7667 Final accuracy training:71.17%, final loss training 0.7616284489631653

Final accuracy test:70.08%, final loss test 0.7736933827400208

import pandas as pd

304/304

history\_df = pd.DataFrame(norm\_history.history)# this is the df to be plotted print(history\_df.head(5))

history\_df.plot(title="Training History") # This will include accuracy, loss, val\_accuracy, val\_loss

plt.xlabel("Epoch")

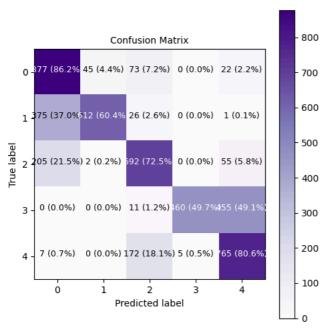
plt.ylabel("Value")

plt.show()

```
₹
        accuracy
                      loss val_accuracy val_loss
     0 0.240432
                  1.603966
                                0.443416 1.540964
       0.288169
                  1.508420
                                 0.457407 1.395892
       0.328549
                                0.475103 1.247865
                  1.387011
     3 0.359465 1.312532
                                0.539095 1.145403
     4 0.383642 1.269821
                                0.554938 1.123342
                                     Training History
         1.6
                                                                  accuracy
                                                                  loss
                                                                  val_accuracy
         1.4
                                                                  val_loss
         1.2
        1.0
         0.8
         0.6
         0.4
         0.2
                           10
                                        20
                                                                40
                                                                             50
                                                    30
               0
                                            Epoch
# Make predictions with the most recent model
y_probs = model.predict(x_test.batch(32))
# View the first 5 predictions
y_probs[:5]
→ 152/152 -
                                 - 2s 5ms/step
     array([[1.4606766e-01, 2.4207935e-02, 5.2395403e-01, 3.7813585e-02,
             2.6795673e-01],
            [3.8323224e-01, 5.1168877e-01, 1.0506588e-01, 1.2268312e-08,
             1.3072181e-05],
            [4.9538244e-03, 3.6125540e-04, 2.0249189e-01, 2.2080423e-01,
             5.7138878e-01],
            [5.0246549e-01, 1.9186155e-01, 3.0062118e-01, 6.9909336e-05,
             4.9820235e-03],
            [4.9976209e-01, 1.8972465e-01, 3.0493146e-01, 8.1613674e-05,
             5.5001150e-03]], dtype=float32)
y_preds = y_probs.argmax(axis=1)
y_preds[:10]
\rightarrow array([2, 1, 4, 0, 0, 2, 0, 1, 0, 0])
# get the true labels from the tuples of the x_test
y_true = [label.numpy() for _, label in x_test]
# Check out the non-prettified confusion matrix
from sklearn.metrics import confusion_matrix
{\tt confusion\_matrix}(y\_{\tt true} = y\_{\tt true},
                 y_pred=y_preds)
→ array([[877, 45, 73,
                              0,
                                  22],
            [375, 612, 26,
                              0,
                                  1],
            [205,
                    2, 692,
                              0, 55],
               0,
                    0, 11, 460, 455],
            [ 7,
                    0, 172,
                              5, 765]])
\mbox{\tt\#} grafica de un img random con traduccion.
# Plot confusion matrix function
import itertools
import numpy as np
figsize = (5, 5)
# Create the confusion matrix
cm = confusion_matrix(y_true, tf.round(y_preds))
cm_norm = cm.astype("float") / cm.sum(axis=1)[:, np.newaxis] # normalize it.
n_classes = cm.shape[0]
```

```
# Let's prettify it
fig, ax = plt.subplots(figsize=figsize)
# Create a matrix plot
cax = ax.matshow(cm, cmap=plt.cm.Purples)
# ax.matshow() creates a matrix plot of the confusion matrix cm
fig.colorbar(cax) # Adds a color bar to the plot
# Create classes
classes = False
if classes:
  labels = classes
  labels = np.arange(cm.shape[0])
# Label the axes
ax.set(title="Confusion Matrix",
       xlabel="Predicted label",
       ylabel="True label",
       xticks=np.arange(n_classes),
       yticks=np.arange(n_classes),
       xticklabels=labels.
       yticklabels=labels)
# Set x-axis labels to bottom
ax.xaxis.set label position("bottom")
ax.xaxis.tick_bottom() # move the x-axis ticks to the bottom of the plot
# Adjust label size
ax.xaxis.label.set_size(10)
ax.yaxis.label.set_size(10)
ax.title.set_size(10)
# Set threshold for different colors
threshold = (cm.max() + cm.min()) / 2.
# Plot the text on each cell
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(
       i. i.
        f"{cm[i, j]} ({cm_norm[i, j]*100:.1f}%)",
        horizontalalignment="center",
        color="white" if cm[i, j] > threshold else "black",
    )
plt.tight layout()
plt.show() #
plt.close(fig) # frees it so the next cell starts fresh
"""Function adapted/taken from:1.https://scikit-learn.org/stable/modules/generated/sklearn.metrics.plot_confusion_matrix.html,
  2. \  \  \, \underline{\text{https://github.com/GokuMohandas/MadeWithML/blob/main/notebooks/08\_Neural\_Networks.ipynb} \\
```

3. Tensorflow and DL with Python https://www.youtube.com/watch?v=tpCFfeUEGs8&ab\_channel=DanielBourke """



**→** 

'Function adapted/taken from:1.https://scikit-learn.org/stable/modules/generated/sklearn.metrics.plot\_confusion\_matrix.html,\n 2. https://github.com/GokuMohandas/MadeWithML/blob/main/notebooks/08\_Neural\_Networks.ipynb\n 3. Tensorflow and DL with Python http c.//www.voutube.com/watch?v=tnCEfallEGc88ah.channal=DanialRounka

```
uei proc_iaiiuom_rmage_iiom_uacasec(mouer, uacasec, crasses).
    # Pick a random example
    dataset = dataset.shuffle(1000) # shuffle to get randomness
    image, true_label = next(iter(dataset.take(1))) # creates an iterator over this dataset.retrieves the next item from this iterator,
    # Predict
    pred\_probs = model.predict(image[None, \dots]) \quad \# \ image[None, \dots] \ changes \ the \ shape \ to \ (96, \ 96, \ 1). \ None \ creates \ a \ new \ axis \ of \ size \ 1.
    # image[None].shape is (1, 96, 96, 1)
    # shorthand for writing out all the slices explicitly, i.e. image[None, :, :, :]
    # image[None, ...] \rightarrow (1, 96, 96, 1)
    print(pred_probs)
    pred_label = classes[pred_probs.argmax()]
    plt.imshow(image.numpy().squeeze(), cmap='gray')
    color = "green" if pred_label == classes[true_label.numpy()] else "red"
    plt.xlabel(f"Pred: {pred_label}"
              f"(True: {classes[true_label.numpy()]})", color=color)
    plt.show()
    plt.close()
# Call it
plot_random_image_from_dataset(model, test_data, classes=[0, 1, 2, 3, 4])
                              - 0s 88ms/step
     [[1.82170545e-09 1.12942974e-10 4.29773150e-04 9.62761045e-01
       3.68091464e-02]]
      20
```

