## PRÁCTICA 6

Mi objetivo en esta práctica ha sido conseguir una red con el mayor accuracy posible llegando a superar el 98% en validación.

```
In [ ]: import torch
        import pathlib
        import numpy as np
        import pandas as pd
        import librosa as lr
        import sounddevice as sd
        import matplotlib.pyplot as plt
        from torch import nn, optim
        from dataclasses import dataclass
        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from tqdm import tqdm
        from train net import train
        from scipy.io.wavfile import write
        from torch.utils.data import TensorDataset, DataLoader
        TRAIN = True
In [ ]: def preprocess_audio(filename, spec_params):
            Preprocesses an audio file to a mel spectrogram.
            Parameters
            filename (str): The path to the audio file.
            spec_params (dataclass): The parameters for calculating the spectrogram.
            Returns
```

```
S_dB (np.array): The mel spectrogram of the audio file.
    audio, sample_rate = lr.load(filename, sr=spec_params.sample_rate)
    audio, _ = lr.effects.trim(audio)
   if len(audio) < 0.1 * sample rate:</pre>
        return None
    if len(audio) < spec_params.target_length:</pre>
        audio = np.pad(audio, (0, spec_params.target_length - len(audio)), "constant")
    else:
        audio = audio[: spec_params.target_length]
   S = lr.feature.melspectrogram(
        y=audio,
        sr=sample_rate,
        n_mels=spec_params.n_mels,
        n_fft=spec_params.n_fft,
       win_length=spec_params.window_length,
        hop length=round(spec params.window length / 2),
   S_dB = 20 * np.log10(S + 1e-6)
   S dB = (S dB - np.max(S dB)) / (np.max(S dB) - np.min(S dB))
    return S_dB
def create_dataset(audios_folder, data_labels, spec_params):
   Creates a dataset from the audio files in a folder.
    Parameters
    audios_folder (str): The path to the folder with the audio files.
    data_labels (dict): A dictionary with the labels for each class.
    spec_params (dataclass): The parameters for calculating the dataset spectrograms.
```

```
Returns
    dataset (TensorDataset): The dataset with the mel spectrograms and labels.
    print(f"\nCreating dataset from {audios_folder}...")
    audio files = pathlib.Path(audios folder).rglob("*.wav")
   # audio_files = list(audio_files)[:1000]
    audios_df = pd.DataFrame({"filename": list(audio_files)})
    audios_df["label"] = audios_df.filename.apply(lambda x: str(x).split("/")[-2])
    audios df["value"] = audios df.label.map(data labels)
    specgrams = []
   labels = []
   filenames = []
   for _, audio in tqdm(audios_df.iterrows(), total=len(audios_df)):
        specgram = preprocess audio(audio["filename"], spec params)
        if specgram is None:
            continue
        labels.append((audio["value"]))
        specgrams.append(specgram[np.newaxis, :, :])
        filenames.append(audio["filename"])
   X tensor = torch.tensor(np.array(specgrams), dtype=torch.float32)
   Y_tensor = torch.tensor(np.array(labels), dtype=torch.long)
    dataset = TensorDataset(X_tensor, Y_tensor)
    return dataset, filenames
def show_dataset_samples(dataset, spec_params, nrows=3, ncols=3):
    Shows a grid of samples from the dataset.
```

```
Parameters
    dataset (TensorDataset): The dataset with the mel spectrograms and labels.
    spec_params (dataclass): The parameters for calculating the spectrogram.
   nrows (int): The number of rows in the grid.
   ncols (int): The number of columns in the grid.
    _, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=(10, 10))
   for i in range(nrows):
        for j in range(ncols):
            idx = np.random.randint(0, len(dataset))
            specgram, label = dataset[idx]
            lr.display.specshow(
                specgram[0].numpy(),
                sr=spec_params.sample_rate,
                hop_length=round(spec_params.window_length / 2),
                ax=axes[i, j],
            axes[i, j].set_title(label.item())
    plt.tight_layout()
    plt.show()
def test net(dataset path, data labels, spec params, net):
   Tests a neural network with a dataset. Prints the accuracy,
    confusion matrix and wrong predictions.
    Parameters
    dataset_path (str): The path to the dataset.
    data_labels (dict): A dictionary with the labels for each class.
    spec params (dataclass): The parameters for calculating the dataset spectrograms.
    net (nn.Module): The neural network to test.
    0.000
```

```
print(f"Testing net with {dataset_path}:\n")
test_dataset, filenames = create_dataset(dataset_path, data_labels, spec_params)
testloader = DataLoader(test dataset, batch size=1, shuffle=False)
net.eval()
predictions = []
real_values = []
with torch.no grad():
    for num in testloader:
        net output = net(num[0])
        predictions.append(torch.argmax(net output).item())
        real values.append(num[1].item())
conf_matrix = confusion_matrix(real_values, predictions)
cm_display = metrics.ConfusionMatrixDisplay(
    conf_matrix, display_labels=data_labels.keys()
accuracy = np.trace(conf matrix) / np.sum(conf matrix)
print(f"\nAccuracy: {accuracy * 100}%")
# print wrong predictions
print("\nWrong predictions:")
for i in range(len(predictions)):
    if real values[i] != predictions[i]:
        print(
            f"Prediction: {predictions[i]}, Real: {real_values[i]}, File: {filenames[i]}"
print("\nConfusion Matrix:")
cm display.plot()
cm display.ax .set title(f"Confusion Matrix {dataset path}")
cm_display.ax_.set_xlabel("Predicted")
cm_display.ax_.set_ylabel("Real")
cm_display.figure_.set_size_inches(9, 7)
plt.show()
```

```
class ConvLayer(nn.Sequential):
    def __init__(self, input_feat, out_feat, max_pool=True):
        lavers = []
        layers.append(nn.Conv2d(input feat, out feat, 3, padding=1))
        layers.append(nn.BatchNorm2d(out feat))
        layers.append(nn.ReLU())
        if max_pool:
            layers.append(nn.MaxPool2d(3, 2, padding=1))
        super(). init (*layers)
class FlattenLayer(nn.Module):
    def forward(self, x):
        return torch.flatten(x, start_dim=1)
class DigitClassifierNet(nn.Sequential):
    def init (self, dropoutProb=0.2, num classes=10):
        input channels = 1
        numF = 16
        timePoolSize = int(np.ceil(74 / 8))
        lavers = []
        layers.append(ConvLayer(input_channels, numF))
        layers.append(ConvLayer(numF, 2 * numF))
        layers.append(ConvLayer(2 * numF, 4 * numF))
        layers.append(ConvLayer(4 * numF, 4 * numF, max_pool=False))
        layers.append(ConvLayer(4 * numF, 4 * numF, max_pool=False))
        layers.append(nn.MaxPool2d((1, timePoolSize)))
        layers.append(nn.Dropout2d(dropoutProb))
        layers.append(FlattenLayer())
        layers.append(nn.Linear(64 * 4, num_classes))
        super().__init__(*layers)
```

```
In [ ]: @dataclass
    class SpectrogramParams:
```

```
n_mels: int
    sample_rate: int
   frame_duration: float
   window_length: int
   n_fft: int
   target_length: int
target_duration = 1.1 # target duration in seconds
frame_duration = 0.03 # frame duration in seconds
sample_rate = 16000
window_length = round(frame_duration * sample_rate)
spec_params = SpectrogramParams(
    n_{mels=32}
   sample_rate=16000,
   frame_duration=frame_duration,
   window_length=window_length,
   n_fft=2 ** (round(window_length) - 1).bit_length(),
   target_length=round(target_duration * sample_rate),
data_labels = {
   "cero": 0,
   "uno": 1,
   "dos": 2,
   "tres": 3,
   "cuatro": 4,
   "cinco": 5,
   "seis": 6,
   "siete": 7,
   "ocho": 8,
   "nueve": 9,
if TRAIN:
   training_dataset, _ = create_dataset(
        "audio_data/training", data_labels, spec_params
```

```
validation_dataset, _ = create_dataset(
    "audio_data/validation", data_labels, spec_params
torch.save(training_dataset, "training_dataset.pt")
torch.save(validation_dataset, "validation_dataset.pt")
device = "cpu"
learning_rate = 0.001
batch size = 512
net = DigitClassifierNet()
optimizer = optim.Adam(net.parameters(), lr=learning_rate)
loss_fn = nn.CrossEntropyLoss()
num_epochs = 30
train_dataloader = DataLoader(training_dataset, batch_size=batch_size, shuffle=True)
val_dataloader = DataLoader(
    validation dataset, batch size=batch size, shuffle=False
print("\nTraining net:")
train losses, val losses, train acc, val acc = train(
    net,
    loss_fn,
   train_dataloader,
    val_dataloader,
    optimizer,
    num_epochs,
    device=device,
torch.save(net.state_dict(), "digit_classifier_net.pth")
fig, axes = plt.subplots(2, 1)
axes[0].plot(train_losses, label="train loss")
axes[0].plot(val losses, label="val loss")
```

```
axes[0].legend()
axes[0].set_xlabel("epoch")
axes[0].set_ylabel("Loss")

axes[1].plot(train_acc, label="train_acc")
axes[1].plot(val_acc, label="val acc")
axes[1].legend()
axes[1].set_xlabel("epoch")
axes[1].set_ylabel("Accuracy")

Creating dataset from audio_data/training...

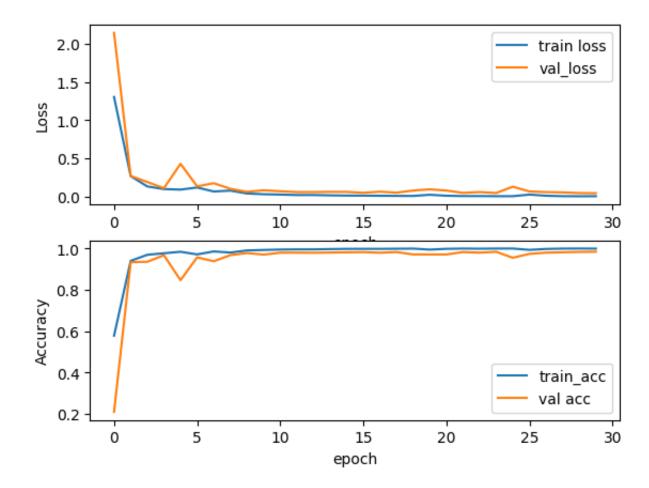
100%| 12812/12812 [00:33<00:00, 380.81it/s]
Creating dataset from audio_data/validation...

100%| 3082/3082 [00:07<00:00, 414.46it/s]</pre>
```

Training Progress: 100%| 30/30 [07:02<00:00, 14.07s/it, Train Loss=0.00469, Val Loss=0.0437, Train Acc

Training net:

=0.999, Val Acc=0.984, Best Val Acc=0.984]



Para testear la red he clasificado los digitos de un dataset distinto al de entrenamiento y de validación. En el caso de este dataset de 80 dígitos vemos como la red obtiene un accuracy del 100% sin fallar un solo dígito. También he hecho la matriz de confusión tanto del nuevo dataset como del dataset de validación y marcado las predicciones incorrectas indicando a que grabación corresponden, para obtener información sobre que está fallando y así poder mejorar aún más la red en un futuro.

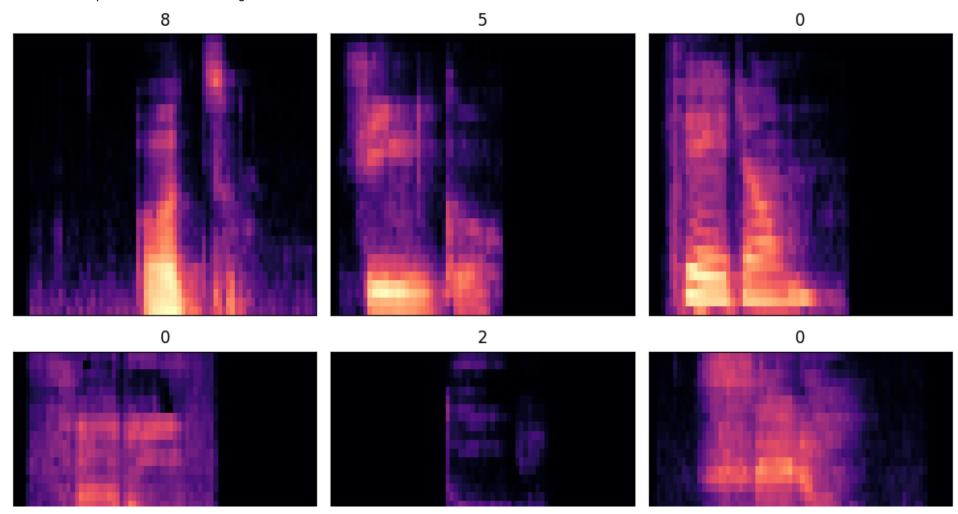
```
In []: training_dataset = torch.load("training_dataset.pt")
    validation_dataset = torch.load("validation_dataset.pt")
    print("Random samples from training dataset")
    show_dataset_samples(training_dataset, spec_params)
```

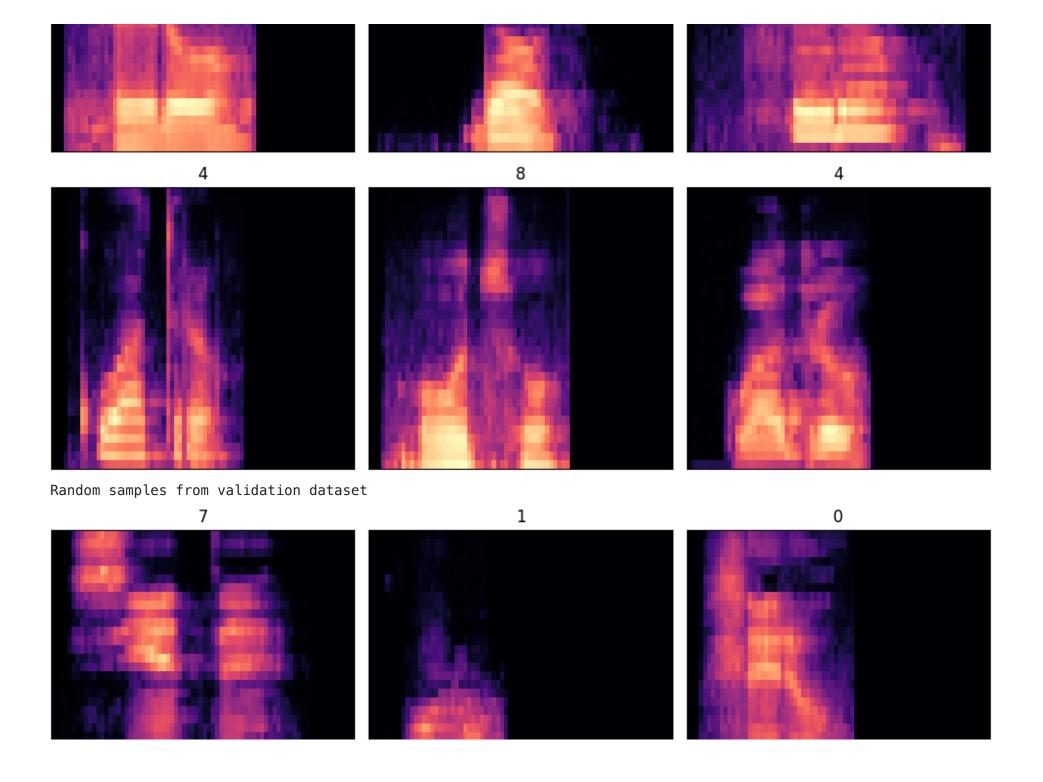
```
print("Random samples from validation dataset")
show_dataset_samples(validation_dataset, spec_params)

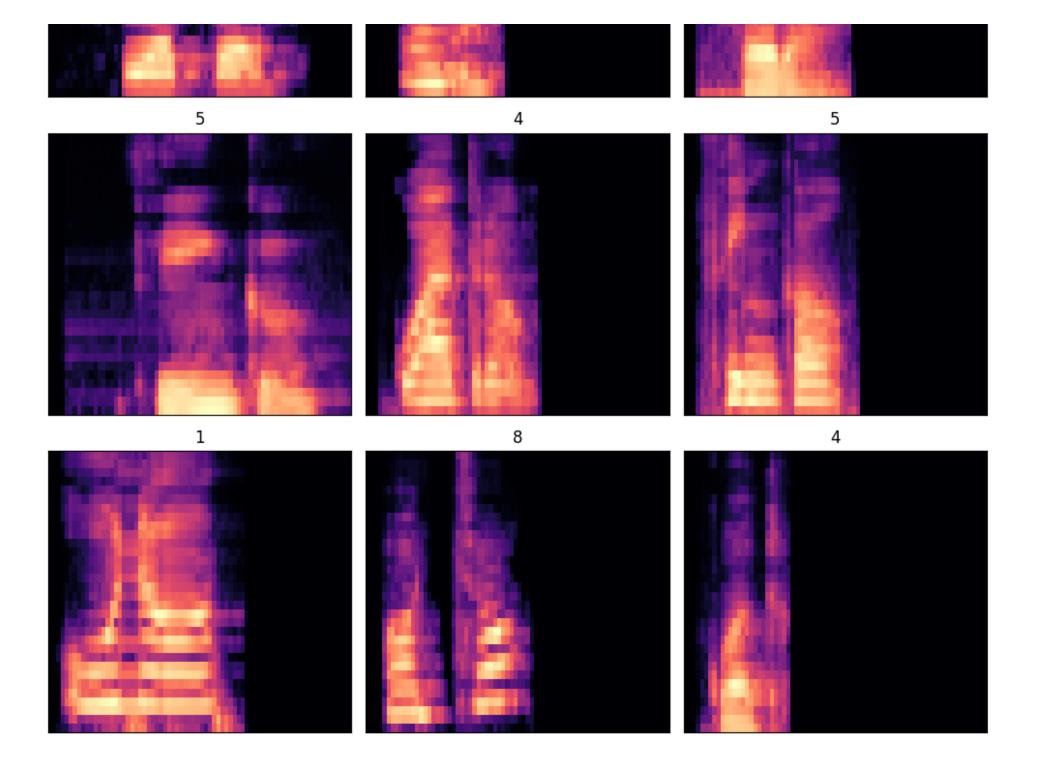
# load our net
net = DigitClassifierNet()
net.load_state_dict(torch.load("digit_classifier_net.pth"))

# test the model
test_net("audio_data/test", data_labels, spec_params, net)
test_net("audio_data/validation", data_labels, spec_params, net)
```

Random samples from training dataset







Testing net with audio\_data/test:

Creating dataset from audio\_data/test...

100%| 80/80 [00:00<00:00, 300.57it/s]

Accuracy: 100.0%

Wrong predictions:

Confusion Matrix:

Confusion Matrix audio\_data/test cero - 7 uno -dos -- 6 tres -- 5 cuatro -- 4 cinco -- 3 seis -siete -- 2 ocho -- 1 nueve cuatro cinco seis siete dos ocho nueve cero uno tres Predicted

Creating dataset from audio\_data/validation...

```
100% | 3082/3082 [00:10<00:00, 306.11it/s]
```

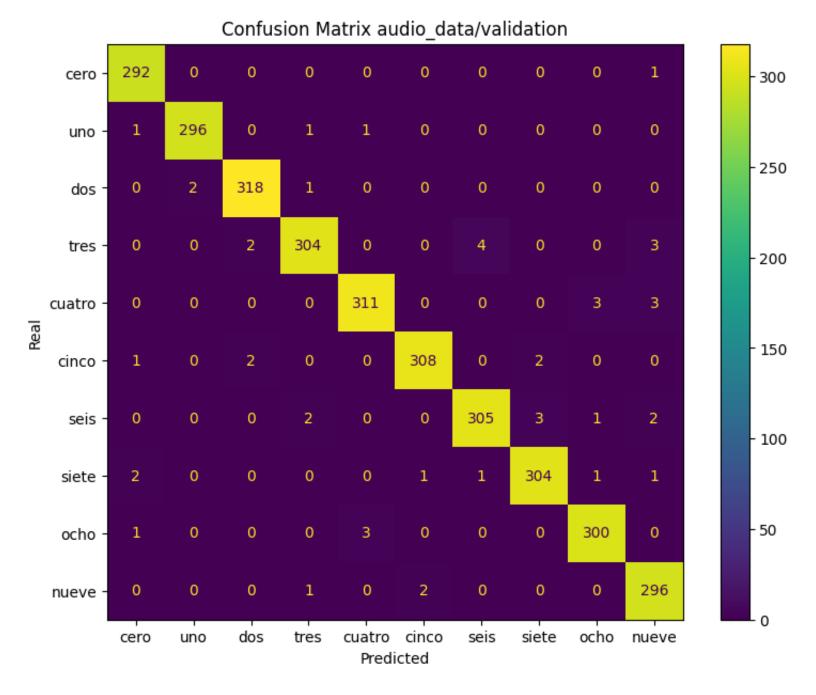
Accuracy: 98.44256975989617%

```
Wrong predictions:
Prediction: 3, Real: 6, File: audio data/validation/seis/2023 056 AB seis 5 4.wav
Prediction: 7, Real: 6, File: audio data/validation/seis/2023 056 AB seis 4 3.wav
Prediction: 7, Real: 6, File: audio data/validation/seis/2023 103 AB seis 1 4.wav
Prediction: 8, Real: 6, File: audio data/validation/seis/2023 027 AB seis 38 19.wav
Prediction: 9, Real: 6, File: audio data/validation/seis/2023 103 AB seis 5 3.wav
Prediction: 3, Real: 6, File: audio_data/validation/seis/2023_103_AB_seis_5_4.wav
Prediction: 7, Real: 6, File: audio_data/validation/seis/2023_012_AB_seis_2_4.wav
Prediction: 9, Real: 6, File: audio data/validation/seis/2023 131 AB seis 2 2.wav
Prediction: 3, Real: 2, File: audio data/validation/dos/2023 012 AB dos 5 4.wav
Prediction: 1, Real: 2, File: audio data/validation/dos/2023 027 AB dos 13 7.wav
Prediction: 1, Real: 2, File: audio data/validation/dos/2023 027 AB dos 33 17.wav
Prediction: 5, Real: 7, File: audio data/validation/siete/2023 125 AB siete 10 2.wav
Prediction: 9, Real: 7, File: audio_data/validation/siete/2023_103_AB_siete_5_3.wav
Prediction: 0, Real: 7, File: audio_data/validation/siete/2023_125_AB_siete_10_1.wav
Prediction: 6, Real: 7, File: audio data/validation/siete/2023 096 AB siete 3 4.wav
Prediction: 0, Real: 7, File: audio data/validation/siete/2023 012 AB siete 1 4.wav
Prediction: 8, Real: 7, File: audio_data/validation/siete/2023_027_AB_siete_32_16.wav
Prediction: 4, Real: 8, File: audio data/validation/ocho/2023 125 AB ocho 11 1.way
Prediction: 0, Real: 8, File: audio data/validation/ocho/2023 027 AB ocho 32 16.wav
Prediction: 4, Real: 8, File: audio_data/validation/ocho/2023_103_AB_ocho_5_4.wav
Prediction: 4, Real: 8, File: audio_data/validation/ocho/2023_103_AB_ocho_5_3.wav
Prediction: 5, Real: 9, File: audio data/validation/nueve/2023 027 AB nueve 38 19.way
Prediction: 3, Real: 9, File: audio data/validation/nueve/2023 012 AB nueve 5 2.wav
```

Prediction: 5, Real: 9, File: audio\_data/validation/nueve/2023\_012\_AB\_nueve\_1\_4.wav Prediction: 6, Real: 3, File: audio\_data/validation/tres/2023\_089\_AB\_tres\_1\_4.wav Prediction: 2, Real: 3, File: audio\_data/validation/tres/2023\_089\_AB\_tres\_3\_1.wav Prediction: 9, Real: 3, File: audio\_data/validation/tres/2023\_103\_AB\_tres\_4\_1.wav Prediction: 6, Real: 3, File: audio\_data/validation/tres/2023\_103\_AB\_tres\_4\_4.wav Prediction: 2, Real: 3, File: audio\_data/validation/tres/2023\_096\_AB\_tres\_3\_1.wav Prediction: 6, Real: 3, File: audio\_data/validation/tres/2023\_000\_AB\_tres\_1\_4.wav Prediction: 6, Real: 3, File: audio\_data/validation/tres/2023\_135\_AB\_tres\_1\_4.wav Prediction: 6, Real: 3, File: audio\_data/validation/tres/2023\_135\_AB\_tres\_1\_4.wav

```
Prediction: 9, Real: 3, File: audio data/validation/tres/2023 056 AB tres 4 2.wav
Prediction: 9, Real: 3, File: audio_data/validation/tres/2023_056_AB_tres_4_3.wav
Prediction: 7, Real: 5, File: audio_data/validation/cinco/2023_027_AB_cinco_32_16.wav
Prediction: 2, Real: 5, File: audio data/validation/cinco/2023 131 AB cinco 3 3.wav
Prediction: 7, Real: 5, File: audio data/validation/cinco/2023 056 AB cinco 4 4.wav
Prediction: 2, Real: 5, File: audio data/validation/cinco/2023 131 AB cinco 3 4.wav
Prediction: 0, Real: 5, File: audio data/validation/cinco/2023 142 AB cinco 2 2.wav
Prediction: 9, Real: 0, File: audio data/validation/cero/2023 103 AB cero 2 3.wav
Prediction: 4, Real: 1, File: audio_data/validation/uno/2023_103_AB_uno_1_4.wav
Prediction: 3, Real: 1, File: audio_data/validation/uno/2023_012_AB_uno_2_4.wav
Prediction: 0, Real: 1, File: audio data/validation/uno/2023 012 AB uno 4 4.wav
Prediction: 9, Real: 4, File: audio data/validation/cuatro/2023 056 AB cuatro 4 1.wav
Prediction: 8, Real: 4, File: audio data/validation/cuatro/2023 027 AB cuatro 13 7.wav
Prediction: 9, Real: 4, File: audio data/validation/cuatro/2023 056 AB cuatro 4 2.wav
Prediction: 9, Real: 4, File: audio data/validation/cuatro/2023 056 AB cuatro 4 4.way
Prediction: 8, Real: 4, File: audio_data/validation/cuatro/2023_027_AB_cuatro_33_17.wav
Prediction: 8, Real: 4, File: audio_data/validation/cuatro/2023_089_AB_cuatro_3_1.wav
```

## Confusion Matrix:



Para probar la red en timepo real simplemente hay que ajustar el tiempo de grabación y ejecutar la celda. La red puede reconocer

varios dígitos presentes en una sola grabación, siempre se deje un pequeño silencio entre dígitos. Los audios con los que se ha entrenado la red estaban muy bien preparados y segmentados, pero al probar la red en tiempo real se nos pueden colar ruidos de fondo y las grabaciones pueden no ser de la mejor calidad, por lo que he utilizado un VAD basado en un modelo ya entrenado para manejar escenarios más complejos https://github.com/snakers4/silero-vad.

```
In [ ]: duration = 8
        freq = 16000
        # load our net
        net = DigitClassifierNet()
        net.load_state_dict(torch.load("digit_classifier_net.pth"))
        # record audio
        record = sd.rec(int(duration * freq), samplerate=freq, channels=1).squeeze()
        sd.wait()
        # load the VAD model
        model, utils = torch.hub.load(repo or dir="snakers4/silero-vad", model="silero vad")
        (get_speech_timestamps, _, read_audio, _, _) = utils
        # get speech timestamps
        speech timestamps = get speech timestamps(record, model, sampling rate=16000)
        # plot the original recorded audio
        plt.plot(np.linspace(0, duration, len(record)), record)
        plt.xlabel("Time [s]")
        # make the predictions for each digit detected
        for timestamp in speech_timestamps:
            # save the detected digit
            digit = record[timestamp["start"] : timestamp["end"]]
            write("file.wav", freq, digit)
            # preprocess the audio
            S = preprocess audio("file.wav", spec params)
            # make the prediction
```

```
x = torch.from_numpy(S.astype(np.float32))
x = x.unsqueeze(0).unsqueeze(0)
x = x.to("cpu")
y = net(x)
y = torch.nn.functional.softmax(y, dim=1)

# get the prediction and the probability
prediction_probability = torch.max(y).item()
prediction = torch.argmax(y).item()

if prediction_probability > 0:
    print(
        f"Prediction: {prediction} , with probability of {prediction_probability * 100:.2f}%"
)

# add vertical lines to visualize the detected digits
plt.axvline(x=timestamp["start"] / freq, color="r", linestyle="--")
plt.axvline(x=timestamp["end"] / freq, color="r", linestyle="--")
plt.show()
```

```
Using cache found in /Users/joan/.cache/torch/hub/snakers4_silero-vad_master
Prediction: 0 , with probability of 99.95%
Prediction: 5 , with probability of 99.71%
Prediction: 8 , with probability of 99.99%
Prediction: 6 , with probability of 99.81%
```

