

Chromagram-Only CNN

March 23, 2025

1 CNN for Chromagram (30 secs)

1.1 1 - All the imports

```
[1]: import os
import numpy as np
from sklearn.model_selection import train_test_split
import tensorflow as tf
import matplotlib.pyplot as plt
```

2025-03-23 00:53:49.625232: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.

1.2 2 - Put the data within the model

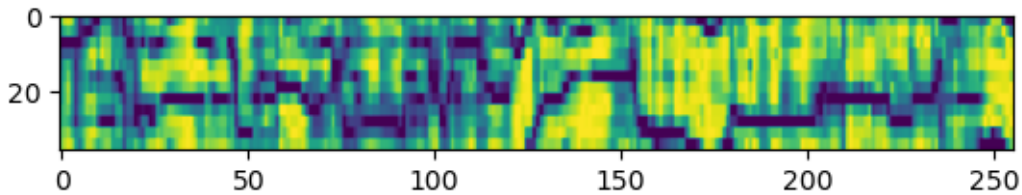
```
[2]: # Import a single image and save it to be read by the model

image = os.path.join('blues.00000.png')

# Load the image
image = tf.io.read_file(image)

# Convert to a numpy array
image = tf.image.decode_png(image, channels=1)
image = tf.image.convert_image_dtype(image, tf.float32)
image = tf.image.resize(image, [36, 256])
image = image.numpy()

plt.imshow(image.reshape(36, 256))
plt.show()
```



2 3 - Create the model

```
[3]: from tensorflow.keras import models
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

model = models.Sequential([
    Conv2D(36, (3, 3), activation='relu', input_shape=(36, 256, 1)),
    MaxPooling2D((2, 2)),

    Flatten(),

    Dense(512, activation='relu'),
    Dropout(0.5),

    Dense(256, activation='relu'),
    Dropout(0.5),

    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])
```

/opt/conda/lib/python3.12/site-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
[4]: model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 34, 254, 36)	360

max_pooling2d (MaxPooling2D)	(None, 17, 127, 36)	0
flatten (Flatten)	(None, 77724)	0
dense (Dense)	(None, 512)	39,795,200
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32,896
dense_3 (Dense)	(None, 10)	1,290

Total params: 39,961,074 (152.44 MB)

Trainable params: 39,961,074 (152.44 MB)

Non-trainable params: 0 (0.00 B)

3 4 - Load the images

```
[5]: # Load the images from Data/spectrograms/spectrograms_256

# Data/spectrograms/spectrogram_256

GENRES = ['blues', 'classical', 'country', 'disco', 'hiphop', 'jazz', 'metal', 'pop', 'reggae', 'rock']

# GENRES = ["classical", "hiphop", "jazz", "metal", "pop", "rock"]
FILE_PATH = os.path.join('Data', 'chromagrams', 'chromagram_24')
X = []
y = []

GENRE_TO_INDEX = {genre: index for index, genre in enumerate(GENRES)}

for genre in GENRES:
    genre_dir = os.path.join(FILE_PATH, genre)
    print(f"Going through {genre}")
    for file in os.listdir(genre_dir):
```

```

try:
    image = tf.io.read_file(os.path.join(genre_dir, file))
    image = tf.image.decode_png(image, channels=1)
    image = tf.image.convert_image_dtype(image, tf.float32)
    image = tf.image.resize(image, [36, 256])
    image = image.numpy()
    X.append(image)
    y.append(GENRE_TO_INDEX[genre])
except:
    pass

X = np.array(X)
y = np.array(y)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪random_state=42)

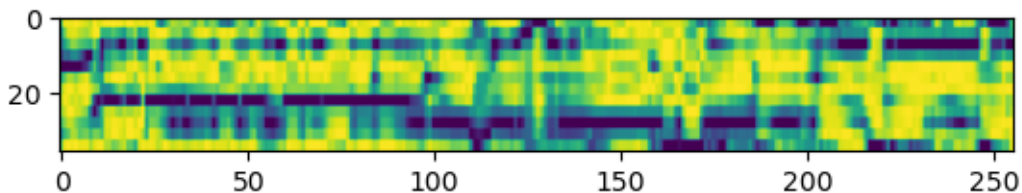
```

Going through blues
 Going through classical
 Going through country
 Going through disco
 Going through hiphop
 Going through jazz
 Going through metal
 Going through pop
 Going through reggae
 Going through rock

```

[6]: # Show image as a sanity check
import matplotlib.pyplot as plt
plt.imshow(X_train[22].reshape(36, 256))
plt.show()

```



```

[7]: model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
    ↪metrics=['accuracy'])

```

```

[8]: model.fit(X_train, y_train, epochs=20, validation_data=(X_test, y_test),
    ↪batch_size=32)

```

Epoch 1/20
25/25 8s 243ms/step -
accuracy: 0.1014 - loss: 5.1020 - val_accuracy: 0.0850 - val_loss: 2.3226
Epoch 2/20
25/25 6s 232ms/step -
accuracy: 0.1047 - loss: 2.3707 - val_accuracy: 0.0800 - val_loss: 2.3117
Epoch 3/20
25/25 6s 226ms/step -
accuracy: 0.1017 - loss: 2.3154 - val_accuracy: 0.0650 - val_loss: 2.3074
Epoch 4/20
25/25 6s 224ms/step -
accuracy: 0.0764 - loss: 2.3064 - val_accuracy: 0.1500 - val_loss: 2.3038
Epoch 5/20
25/25 6s 221ms/step -
accuracy: 0.1167 - loss: 2.3003 - val_accuracy: 0.1450 - val_loss: 2.3025
Epoch 6/20
25/25 6s 221ms/step -
accuracy: 0.1202 - loss: 2.2898 - val_accuracy: 0.0750 - val_loss: 2.2954
Epoch 7/20
25/25 6s 221ms/step -
accuracy: 0.1500 - loss: 2.2726 - val_accuracy: 0.1250 - val_loss: 2.2791
Epoch 8/20
25/25 6s 227ms/step -
accuracy: 0.2137 - loss: 2.2218 - val_accuracy: 0.1200 - val_loss: 2.2534
Epoch 9/20
25/25 6s 220ms/step -
accuracy: 0.2190 - loss: 2.1608 - val_accuracy: 0.2100 - val_loss: 2.1533
Epoch 10/20
25/25 6s 222ms/step -
accuracy: 0.2753 - loss: 2.0052 - val_accuracy: 0.2250 - val_loss: 2.0479
Epoch 11/20
25/25 6s 221ms/step -
accuracy: 0.3047 - loss: 1.8244 - val_accuracy: 0.2200 - val_loss: 2.0274
Epoch 12/20
25/25 6s 223ms/step -
accuracy: 0.3744 - loss: 1.7106 - val_accuracy: 0.2500 - val_loss: 2.0426
Epoch 13/20
25/25 6s 225ms/step -
accuracy: 0.4189 - loss: 1.5493 - val_accuracy: 0.2200 - val_loss: 2.1877
Epoch 14/20
25/25 6s 222ms/step -
accuracy: 0.4571 - loss: 1.4623 - val_accuracy: 0.2300 - val_loss: 2.1527
Epoch 15/20
25/25 6s 218ms/step -
accuracy: 0.5285 - loss: 1.2679 - val_accuracy: 0.2500 - val_loss: 2.1360
Epoch 16/20
25/25 6s 220ms/step -
accuracy: 0.6056 - loss: 1.1083 - val_accuracy: 0.2100 - val_loss: 2.2748

```
Epoch 17/20
25/25          6s 220ms/step -
accuracy: 0.6328 - loss: 1.0569 - val_accuracy: 0.2450 - val_loss: 2.2527
Epoch 18/20
25/25          6s 222ms/step -
accuracy: 0.6844 - loss: 0.9294 - val_accuracy: 0.2150 - val_loss: 2.3980
Epoch 19/20
25/25          5s 218ms/step -
accuracy: 0.6957 - loss: 0.8547 - val_accuracy: 0.2700 - val_loss: 2.4271
Epoch 20/20
25/25          6s 227ms/step -
accuracy: 0.7680 - loss: 0.6657 - val_accuracy: 0.2500 - val_loss: 2.4708
```

```
[8]: <keras.src.callbacks.history.History at 0x7f453c1cbce0>
```

```
[9]: evaluation = model.evaluate(X_test, y_test)
      print(f"Test accuracy: {evaluation[1]:.3f}")
```

```
7/7          0s 21ms/step -
accuracy: 0.2742 - loss: 2.3897
Test accuracy: 0.250
```

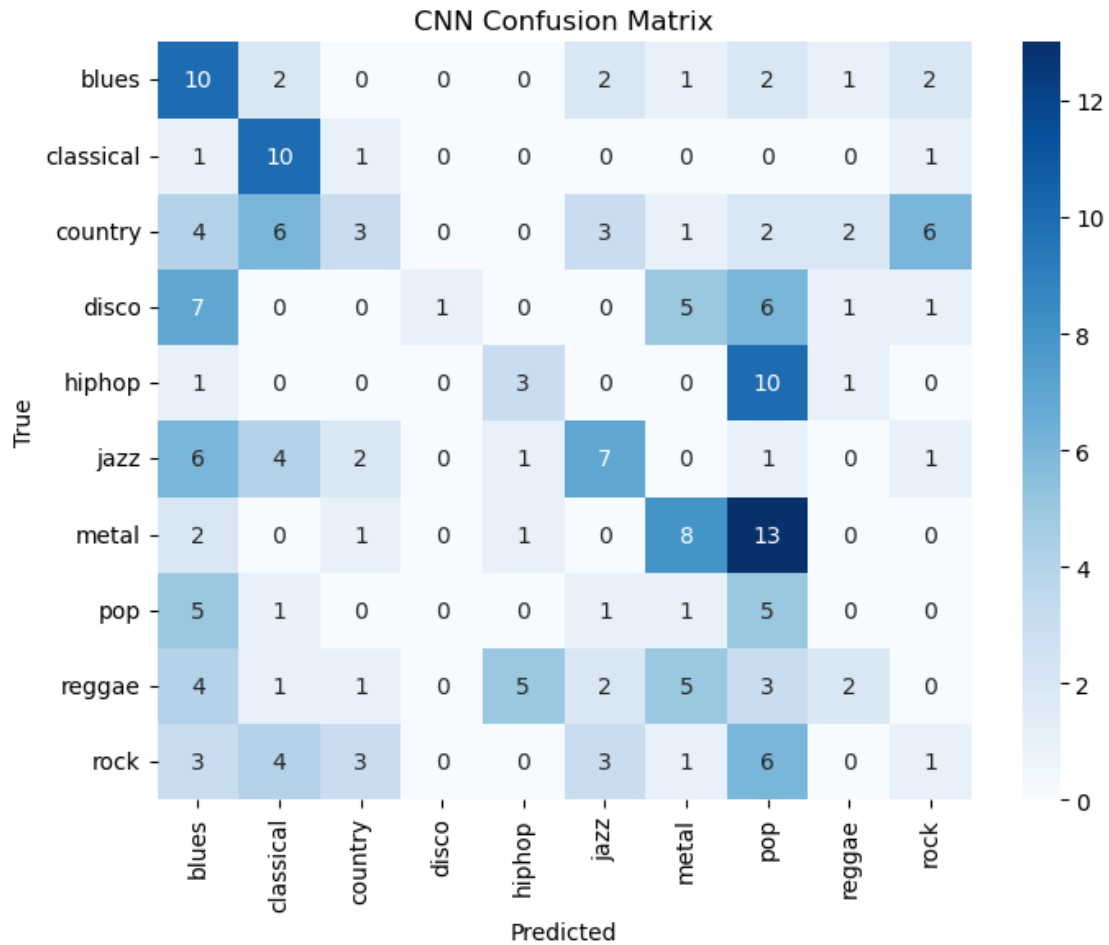
4 Apply the confusion matrix after the model

```
[10]: import seaborn as sns
      # from sklearn.metrics import confusion
      import numpy as NP
      from sklearn.metrics import confusion_matrix

      cnn_preds = np.argmax(model.predict(X_test), axis=1)
      cnn_cm = confusion_matrix(y_test, cnn_preds)

      # Plot the confusion matrix
      plt.figure(figsize=(8, 6))
      sns.heatmap(cnn_cm, annot=True, fmt="d", cmap="Blues", xticklabels=GENRES,
                  yticklabels=GENRES)
      plt.title("CNN Confusion Matrix")
      plt.xlabel("Predicted")
      plt.ylabel("True")
      plt.show()
```

```
7/7          0s 25ms/step
```



4.1 9 - Limited Genres Easy (metal and classical)

```
[11]: import tensorflow as tf
import os
import numpy as np
from sklearn.model_selection import train_test_split

GENRES = ['classical', 'metal']
FILE_PATH = os.path.join('Data', 'chromagrams', 'chromagram_24')
X = []
y = []

GENRE_TO_INDEX = {genre: index for index, genre in enumerate(GENRES)}

# Define the augmentation function
def augment_image(image):
    image = tf.image.random_flip_left_right(image)
```

```

    image = tf.image.random_brightness(image, max_delta=0.1)
    image = tf.image.random_contrast(image, 0.8, 1.2)
    return image

for genre in GENRES:
    genre_dir = os.path.join(FILE_PATH, genre)
    print(f"Going through {genre}")
    for file in os.listdir(genre_dir):
        try:
            image = tf.io.read_file(os.path.join(genre_dir, file))
            image = tf.image.decode_png(image, channels=1)
            image = tf.image.convert_image_dtype(image, tf.float32)
            image = tf.image.resize(image, [36, 256])

            # Apply the augmentation
            image = augment_image(image)
            image = image.numpy() # Convert to numpy array for further
            ↪processing
            X.append(image)
            y.append(GENRE_TO_INDEX[genre])
        except:
            continue

X = np.array(X)
y = np.array(y)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
            ↪random_state=42)

from tensorflow.keras import models
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
            ↪Dropout, Normalization

model = models.Sequential([
    Conv2D(36, (3, 3), activation='relu', input_shape=(36, 256, 1)),
    MaxPooling2D((2, 2)),

    Flatten(),

    Dense(512, activation='relu'),
    Dropout(0.5),

    Dense(256, activation='relu'),
    Dropout(0.5),

    Dense(128, activation='relu'),

```



```

        Dense(10, activation='softmax')
    ])

    from tensorflow.keras.optimizers import Adam
    from tensorflow.keras.callbacks import ReduceLROnPlateau

    model.compile(optimizer=Adam(learning_rate=0.0001),
        ↪loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3,
        ↪min_lr=1e-6)

    model.fit(X_train, y_train, epochs=20, validation_data=(X_test, y_test),
        ↪batch_size=32, callbacks=[reduce_lr])

    evaluation = model.evaluate(X_test, y_test)
    print(f"Test accuracy: {evaluation[1]:.3f}")

```

Going through classical

Going through metal

Epoch 1/20

/opt/conda/lib/python3.12/site-

packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

super().__init__(activity_regularizer=activity_regularizer, **kwargs)

5/5 4s 287ms/step -

accuracy: 0.3340 - loss: 1.7033 - val_accuracy: 0.5250 - val_loss: 0.7077 -
learning_rate: 1.0000e-04

Epoch 2/20

5/5 1s 236ms/step -

accuracy: 0.5170 - loss: 1.0387 - val_accuracy: 0.4750 - val_loss: 0.8331 -
learning_rate: 1.0000e-04

Epoch 3/20

5/5 1s 226ms/step -

accuracy: 0.4319 - loss: 1.3540 - val_accuracy: 0.5250 - val_loss: 0.6840 -
learning_rate: 1.0000e-04

Epoch 4/20

5/5 1s 229ms/step -

accuracy: 0.5292 - loss: 1.1100 - val_accuracy: 0.5250 - val_loss: 0.6997 -
learning_rate: 1.0000e-04

Epoch 5/20

5/5 1s 234ms/step -

accuracy: 0.5501 - loss: 0.9799 - val_accuracy: 0.4750 - val_loss: 0.6944 -
learning_rate: 1.0000e-04

Epoch 6/20

5/5 1s 232ms/step -
 accuracy: 0.4783 - loss: 1.1280 - val_accuracy: 0.4750 - val_loss: 0.7100 -
 learning_rate: 1.0000e-04
 Epoch 7/20
 5/5 1s 228ms/step -
 accuracy: 0.5218 - loss: 1.0522 - val_accuracy: 0.4750 - val_loss: 0.7016 -
 learning_rate: 5.0000e-05
 Epoch 8/20
 5/5 1s 233ms/step -
 accuracy: 0.5344 - loss: 0.9565 - val_accuracy: 0.5250 - val_loss: 0.6973 -
 learning_rate: 5.0000e-05
 Epoch 9/20
 5/5 1s 236ms/step -
 accuracy: 0.5197 - loss: 0.8900 - val_accuracy: 0.5250 - val_loss: 0.6952 -
 learning_rate: 5.0000e-05
 Epoch 10/20
 5/5 1s 238ms/step -
 accuracy: 0.4516 - loss: 0.9227 - val_accuracy: 0.6250 - val_loss: 0.6944 -
 learning_rate: 2.5000e-05
 Epoch 11/20
 5/5 1s 235ms/step -
 accuracy: 0.5172 - loss: 0.9622 - val_accuracy: 0.8750 - val_loss: 0.6964 -
 learning_rate: 2.5000e-05
 Epoch 12/20
 5/5 1s 235ms/step -
 accuracy: 0.4589 - loss: 0.9575 - val_accuracy: 0.4750 - val_loss: 0.7014 -
 learning_rate: 2.5000e-05
 Epoch 13/20
 5/5 1s 225ms/step -
 accuracy: 0.5248 - loss: 0.9377 - val_accuracy: 0.4750 - val_loss: 0.7051 -
 learning_rate: 1.2500e-05
 Epoch 14/20
 5/5 1s 234ms/step -
 accuracy: 0.4797 - loss: 0.9780 - val_accuracy: 0.4750 - val_loss: 0.7067 -
 learning_rate: 1.2500e-05
 Epoch 15/20
 5/5 1s 241ms/step -
 accuracy: 0.4681 - loss: 0.9432 - val_accuracy: 0.4750 - val_loss: 0.7091 -
 learning_rate: 1.2500e-05
 Epoch 16/20
 5/5 1s 230ms/step -
 accuracy: 0.5631 - loss: 0.7753 - val_accuracy: 0.4750 - val_loss: 0.7102 -
 learning_rate: 6.2500e-06
 Epoch 17/20
 5/5 1s 236ms/step -
 accuracy: 0.4733 - loss: 0.9172 - val_accuracy: 0.4750 - val_loss: 0.7105 -
 learning_rate: 6.2500e-06
 Epoch 18/20

```

5/5          1s 241ms/step -
accuracy: 0.4742 - loss: 0.9381 - val_accuracy: 0.4750 - val_loss: 0.7091 -
learning_rate: 6.2500e-06
Epoch 19/20
5/5          1s 237ms/step -
accuracy: 0.4819 - loss: 0.8910 - val_accuracy: 0.4750 - val_loss: 0.7084 -
learning_rate: 3.1250e-06
Epoch 20/20
5/5          1s 241ms/step -
accuracy: 0.4944 - loss: 0.9199 - val_accuracy: 0.4750 - val_loss: 0.7079 -
learning_rate: 3.1250e-06
2/2          0s 12ms/step -
accuracy: 0.4625 - loss: 0.7104
Test accuracy: 0.475

```

4.2 10 - Confusion Matrix Easy (classical and metal)

```

[12]: import seaborn as sns
      # from sklearn.metrics import confusion
      import numpy as NP
      from sklearn.metrics import confusion_matrix

      cnn_preds = np.argmax(model.predict(X_test), axis=1)
      cnn_cm = confusion_matrix(y_test, cnn_preds)

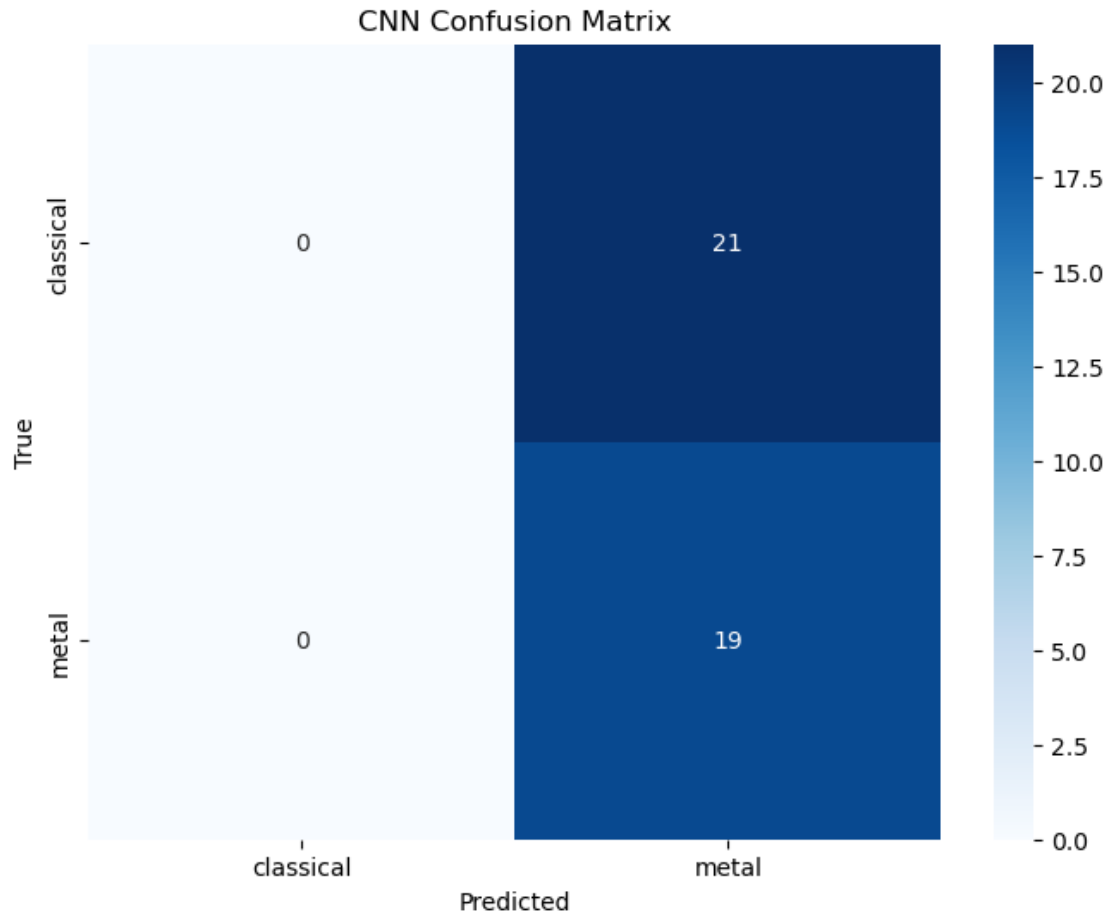
      # Plot the confusion matrix
      plt.figure(figsize=(8, 6))
      sns.heatmap(cnn_cm, annot=True, fmt="d", cmap="Blues", xticklabels=GENRES,
                  yticklabels=GENRES)
      plt.title("CNN Confusion Matrix")
      plt.xlabel("Predicted")
      plt.ylabel("True")
      plt.show()

```

```

2/2          0s 74ms/step

```



4.3 11 - Limited genres Hard (disco and pop)

```
[13]: import tensorflow as tf
import os
import numpy as np
from sklearn.model_selection import train_test_split

GENRES = ['disco', 'pop']
FILE_PATH = os.path.join('Data', 'chromagrams', 'chromagram_24')
X = []
y = []

GENRE_TO_INDEX = {genre: index for index, genre in enumerate(GENRES)}

# Define the augmentation function
def augment_image(image):
    image = tf.image.random_flip_left_right(image)
    image = tf.image.random_brightness(image, max_delta=0.1)
```

```

    image = tf.image.random_contrast(image, 0.8, 1.2)
    return image

for genre in GENRES:
    genre_dir = os.path.join(FILE_PATH, genre)
    print(f"Going through {genre}")
    for file in os.listdir(genre_dir):
        try:
            image = tf.io.read_file(os.path.join(genre_dir, file))
            image = tf.image.decode_png(image, channels=1)
            image = tf.image.convert_image_dtype(image, tf.float32)
            image = tf.image.resize(image, [36, 256])

            # Apply the augmentation
            image = augment_image(image)

            image = image.numpy() # Convert to numpy array for further
            ↪processing
            X.append(image)
            y.append(GENRE_TO_INDEX[genre])
        except:
            continue

X = np.array(X)
y = np.array(y)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
            ↪random_state=42)

from tensorflow.keras import models
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
            ↪Dropout, Normalization

model = models.Sequential([
    Conv2D(36, (3, 3), activation='relu', input_shape=(36, 256, 1)),
    MaxPooling2D((2, 2)),

    Flatten(),

    Dense(512, activation='relu'),
    Dropout(0.5),

    Dense(256, activation='relu'),
    Dropout(0.5),

    Dense(128, activation='relu'),

```

```

        Dense(10, activation='softmax')
    ])

    from tensorflow.keras.optimizers import Adam
    from tensorflow.keras.callbacks import ReduceLROnPlateau

    model.compile(optimizer=Adam(learning_rate=0.0001),
        ↳loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3,
        ↳min_lr=1e-6)

    model.fit(X_train, y_train, epochs=20, validation_data=(X_test, y_test),
        ↳batch_size=32, callbacks=[reduce_lr])

    evaluation = model.evaluate(X_test, y_test)
    print(f"Test accuracy: {evaluation[1]:.3f}")

```

Going through disco

Going through pop

Epoch 1/20

/opt/conda/lib/python3.12/site-

packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

5/5 3s 277ms/step -

accuracy: 0.1928 - loss: 1.9740 - val_accuracy: 0.4750 - val_loss: 0.9608 -
learning_rate: 1.0000e-04

Epoch 2/20

5/5 1s 225ms/step -

accuracy: 0.4950 - loss: 1.2212 - val_accuracy: 0.4750 - val_loss: 0.8810 -
learning_rate: 1.0000e-04

Epoch 3/20

5/5 1s 240ms/step -

accuracy: 0.5171 - loss: 1.3551 - val_accuracy: 0.4750 - val_loss: 0.8399 -
learning_rate: 1.0000e-04

Epoch 4/20

5/5 1s 228ms/step -

accuracy: 0.4961 - loss: 1.1132 - val_accuracy: 0.4750 - val_loss: 0.8405 -
learning_rate: 1.0000e-04

Epoch 5/20

5/5 1s 237ms/step -

accuracy: 0.4424 - loss: 1.0624 - val_accuracy: 0.4750 - val_loss: 0.8511 -
learning_rate: 1.0000e-04

Epoch 6/20

5/5 1s 232ms/step -
 accuracy: 0.4462 - loss: 1.2143 - val_accuracy: 0.4750 - val_loss: 0.7762 -
 learning_rate: 1.0000e-04
 Epoch 7/20
 5/5 1s 229ms/step -
 accuracy: 0.5994 - loss: 0.8669 - val_accuracy: 0.4750 - val_loss: 0.7699 -
 learning_rate: 1.0000e-04
 Epoch 8/20
 5/5 1s 226ms/step -
 accuracy: 0.5282 - loss: 1.0770 - val_accuracy: 0.4750 - val_loss: 0.7946 -
 learning_rate: 1.0000e-04
 Epoch 9/20
 5/5 1s 223ms/step -
 accuracy: 0.4477 - loss: 0.9819 - val_accuracy: 0.4750 - val_loss: 0.8142 -
 learning_rate: 1.0000e-04
 Epoch 10/20
 5/5 1s 228ms/step -
 accuracy: 0.5492 - loss: 0.8298 - val_accuracy: 0.4750 - val_loss: 0.7620 -
 learning_rate: 1.0000e-04
 Epoch 11/20
 5/5 1s 225ms/step -
 accuracy: 0.5530 - loss: 0.9722 - val_accuracy: 0.4750 - val_loss: 0.7400 -
 learning_rate: 1.0000e-04
 Epoch 12/20
 5/5 1s 220ms/step -
 accuracy: 0.5245 - loss: 0.9239 - val_accuracy: 0.4750 - val_loss: 0.7601 -
 learning_rate: 1.0000e-04
 Epoch 13/20
 5/5 1s 220ms/step -
 accuracy: 0.5392 - loss: 0.9345 - val_accuracy: 0.4750 - val_loss: 0.8045 -
 learning_rate: 1.0000e-04
 Epoch 14/20
 5/5 1s 234ms/step -
 accuracy: 0.4549 - loss: 1.0629 - val_accuracy: 0.4750 - val_loss: 0.8449 -
 learning_rate: 1.0000e-04
 Epoch 15/20
 5/5 1s 227ms/step -
 accuracy: 0.4546 - loss: 1.0473 - val_accuracy: 0.4750 - val_loss: 0.8633 -
 learning_rate: 5.0000e-05
 Epoch 16/20
 5/5 1s 223ms/step -
 accuracy: 0.4591 - loss: 0.9554 - val_accuracy: 0.4750 - val_loss: 0.8676 -
 learning_rate: 5.0000e-05
 Epoch 17/20
 5/5 1s 223ms/step -
 accuracy: 0.5253 - loss: 0.8380 - val_accuracy: 0.4750 - val_loss: 0.8564 -
 learning_rate: 5.0000e-05
 Epoch 18/20

```

5/5          1s 226ms/step -
accuracy: 0.5237 - loss: 0.9044 - val_accuracy: 0.4750 - val_loss: 0.8457 -
learning_rate: 2.5000e-05
Epoch 19/20
5/5          1s 233ms/step -
accuracy: 0.5201 - loss: 0.9314 - val_accuracy: 0.4750 - val_loss: 0.8393 -
learning_rate: 2.5000e-05
Epoch 20/20
5/5          1s 228ms/step -
accuracy: 0.5831 - loss: 0.8485 - val_accuracy: 0.4750 - val_loss: 0.8308 -
learning_rate: 2.5000e-05
2/2          0s 10ms/step -
accuracy: 0.4625 - loss: 0.8417
Test accuracy: 0.475

```

4.4 12 - Confusion Matrix Hard (disco and pop)

```

[14]: import seaborn as sns
      # from sklearn.metrics import confusion
      import numpy as NP
      from sklearn.metrics import confusion_matrix

      cnn_preds = np.argmax(model.predict(X_test), axis=1)
      cnn_cm = confusion_matrix(y_test, cnn_preds)

      # Plot the confusion matrix
      plt.figure(figsize=(8, 6))
      sns.heatmap(cnn_cm, annot=True, fmt="d", cmap="Blues", xticklabels=GENRES,
                  yticklabels=GENRES)
      plt.title("CNN Confusion Matrix")
      plt.xlabel("Predicted")
      plt.ylabel("True")
      plt.show()

```

WARNING:tensorflow:5 out of the last 10 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x7f4510371080> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.

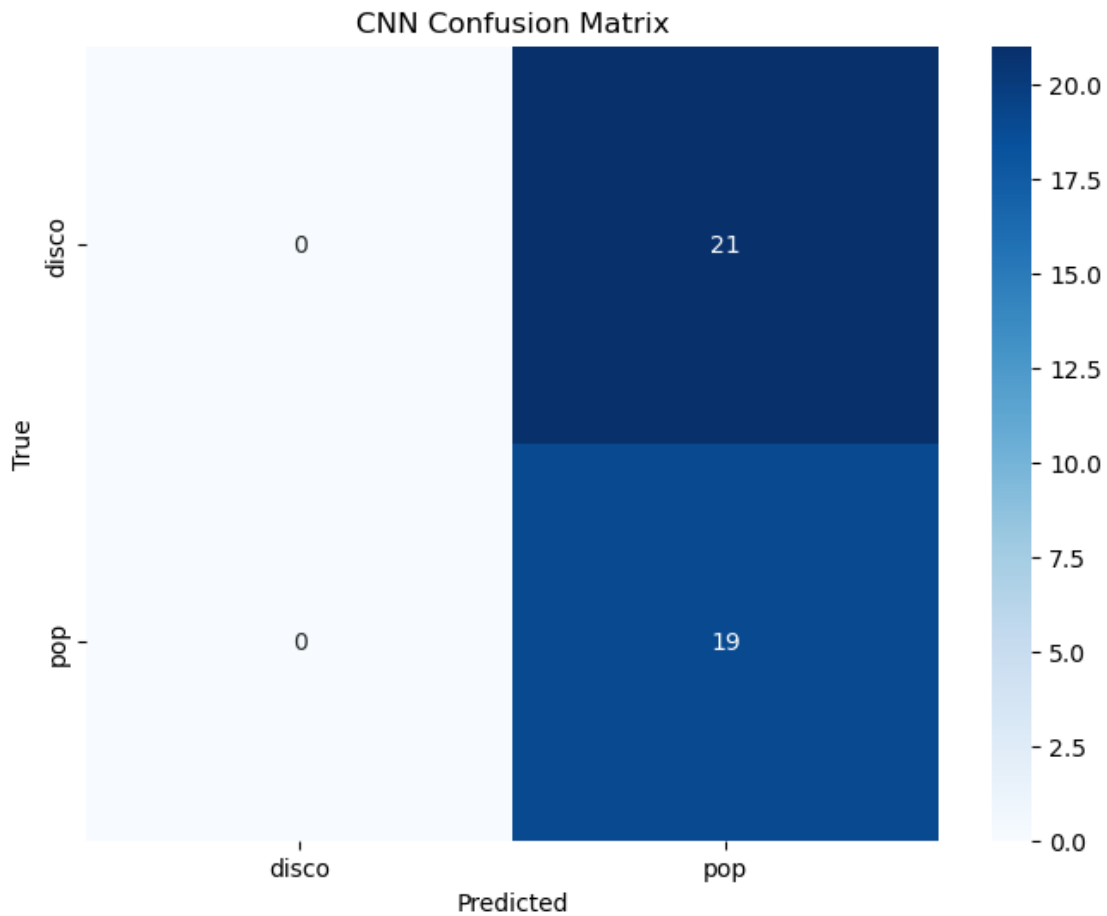
```

1/2          0s
141ms/stepWARNING:tensorflow:6 out of the last 11 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at
0x7f4510371080> triggered tf.function retracing. Tracing is expensive and the

```


excessive number of tracings could be due to (1) creating `@tf.function` repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your `@tf.function` outside of the loop. For (2), `@tf.function` has `reduce_retracing=True` option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.

2/2 0s 159ms/step



4.5 13 - Limited Genres Medium (5 random)

```
[15]: import tensorflow as tf
import os
import numpy as np
from sklearn.model_selection import train_test_split
import random
```

```

GENRES = ['blues', 'classical', 'country', 'disco', 'hiphop', 'jazz', 'metal',
    ↪ 'pop', 'reggae', 'rock']
GENRES = random.sample(GENRES, 5)
print(GENRES)
FILE_PATH = os.path.join('Data', 'chromagrams', 'chromagram_24')
X = []
y = []

GENRE_TO_INDEX = {genre: index for index, genre in enumerate(GENRES)}

# Define the augmentation function
def augment_image(image):
    image = tf.image.random_flip_left_right(image)
    image = tf.image.random_brightness(image, max_delta=0.1)
    image = tf.image.random_contrast(image, 0.8, 1.2)
    return image

for genre in GENRES:
    genre_dir = os.path.join(FILE_PATH, genre)
    print(f"Going through {genre}")
    for file in os.listdir(genre_dir):
        try:
            image = tf.io.read_file(os.path.join(genre_dir, file))
            image = tf.image.decode_png(image, channels=1)
            image = tf.image.convert_image_dtype(image, tf.float32)
            image = tf.image.resize(image, [36, 256])

            # Apply the augmentation
            image = augment_image(image)

            image = image.numpy() # Convert to numpy array for further
            ↪ processing
            X.append(image)
            y.append(GENRE_TO_INDEX[genre])
        except:
            continue

X = np.array(X)
y = np.array(y)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪ random_state=42)

from tensorflow.keras import models
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
    ↪ Dropout, Normalization

```

```

model = models.Sequential([
    Conv2D(36, (3, 3), activation='relu', input_shape=(36, 256, 1)),
    MaxPooling2D((2, 2)),

    Flatten(),

    Dense(512, activation='relu'),
    Dropout(0.5),

    Dense(256, activation='relu'),
    Dropout(0.5),

    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])

from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ReduceLROnPlateau

model.compile(optimizer=Adam(learning_rate=0.0001),
    ↪loss='sparse_categorical_crossentropy', metrics=['accuracy'])
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3,
    ↪min_lr=1e-6)

model.fit(X_train, y_train, epochs=20, validation_data=(X_test, y_test),
    ↪batch_size=32, callbacks=[reduce_lr])

evaluation = model.evaluate(X_test, y_test)
print(f"Test accuracy: {evaluation[1]:.3f}")

```

```
['rock', 'pop', 'country', 'reggae', 'classical']
```

Going through rock

Going through pop

Going through country

Going through reggae

Going through classical

/opt/conda/lib/python3.12/site-

packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Epoch 1/20

13/13 8s 381ms/step -

accuracy: 0.2045 - loss: 2.1218 - val_accuracy: 0.2400 - val_loss: 1.6974 -

```

learning_rate: 1.0000e-04
Epoch 2/20
13/13          4s 324ms/step -
accuracy: 0.1720 - loss: 2.1241 - val_accuracy: 0.2800 - val_loss: 1.6907 -
learning_rate: 1.0000e-04
Epoch 3/20
13/13          4s 339ms/step -
accuracy: 0.1987 - loss: 1.9797 - val_accuracy: 0.1000 - val_loss: 1.7258 -
learning_rate: 1.0000e-04
Epoch 4/20
13/13          4s 335ms/step -
accuracy: 0.1864 - loss: 1.9222 - val_accuracy: 0.1000 - val_loss: 1.7630 -
learning_rate: 1.0000e-04
Epoch 5/20
13/13          4s 332ms/step -
accuracy: 0.2375 - loss: 1.8345 - val_accuracy: 0.2000 - val_loss: 1.6912 -
learning_rate: 1.0000e-04
Epoch 6/20
13/13          4s 340ms/step -
accuracy: 0.2017 - loss: 1.8527 - val_accuracy: 0.1100 - val_loss: 1.7221 -
learning_rate: 5.0000e-05
Epoch 7/20
13/13          5s 344ms/step -
accuracy: 0.1798 - loss: 1.7907 - val_accuracy: 0.1000 - val_loss: 1.7232 -
learning_rate: 5.0000e-05
Epoch 8/20
13/13          5s 348ms/step -
accuracy: 0.1763 - loss: 1.7685 - val_accuracy: 0.1000 - val_loss: 1.7213 -
learning_rate: 5.0000e-05
Epoch 9/20
13/13          5s 348ms/step -
accuracy: 0.2262 - loss: 1.7923 - val_accuracy: 0.1000 - val_loss: 1.7238 -
learning_rate: 2.5000e-05
Epoch 10/20
13/13          4s 339ms/step -
accuracy: 0.1963 - loss: 1.7610 - val_accuracy: 0.1000 - val_loss: 1.7211 -
learning_rate: 2.5000e-05
Epoch 11/20
13/13          5s 346ms/step -
accuracy: 0.2108 - loss: 1.7973 - val_accuracy: 0.1000 - val_loss: 1.7147 -
learning_rate: 2.5000e-05
Epoch 12/20
13/13          5s 361ms/step -
accuracy: 0.2150 - loss: 1.7779 - val_accuracy: 0.1000 - val_loss: 1.7095 -
learning_rate: 1.2500e-05
Epoch 13/20
13/13          7s 460ms/step -
accuracy: 0.2445 - loss: 1.7248 - val_accuracy: 0.1000 - val_loss: 1.7056 -

```

```

learning_rate: 1.2500e-05
Epoch 14/20
13/13          5s 395ms/step -
accuracy: 0.2327 - loss: 1.7318 - val_accuracy: 0.1000 - val_loss: 1.7032 -
learning_rate: 1.2500e-05
Epoch 15/20
13/13          5s 375ms/step -
accuracy: 0.2062 - loss: 1.8017 - val_accuracy: 0.1000 - val_loss: 1.7064 -
learning_rate: 6.2500e-06
Epoch 16/20
13/13          5s 390ms/step -
accuracy: 0.2543 - loss: 1.7272 - val_accuracy: 0.1000 - val_loss: 1.7041 -
learning_rate: 6.2500e-06
Epoch 17/20
13/13          5s 380ms/step -
accuracy: 0.2485 - loss: 1.7268 - val_accuracy: 0.1000 - val_loss: 1.7037 -
learning_rate: 6.2500e-06
Epoch 18/20
13/13          6s 473ms/step -
accuracy: 0.2050 - loss: 1.7424 - val_accuracy: 0.1000 - val_loss: 1.7025 -
learning_rate: 3.1250e-06
Epoch 19/20
13/13          6s 470ms/step -
accuracy: 0.2378 - loss: 1.7495 - val_accuracy: 0.1000 - val_loss: 1.7012 -
learning_rate: 3.1250e-06
Epoch 20/20
13/13          6s 453ms/step -
accuracy: 0.2476 - loss: 1.6992 - val_accuracy: 0.1000 - val_loss: 1.7027 -
learning_rate: 3.1250e-06
4/4            0s 37ms/step -
accuracy: 0.0890 - loss: 1.7119
Test accuracy: 0.100

```

4.6 14 - Confusion Matrix Medium (5 random)

```

[16]: import seaborn as sns
      # from sklearn.metrics import confusion
      import numpy as NP
      from sklearn.metrics import confusion_matrix

      cnn_preds = np.argmax(model.predict(X_test), axis=1)
      cnn_cm = confusion_matrix(y_test, cnn_preds)

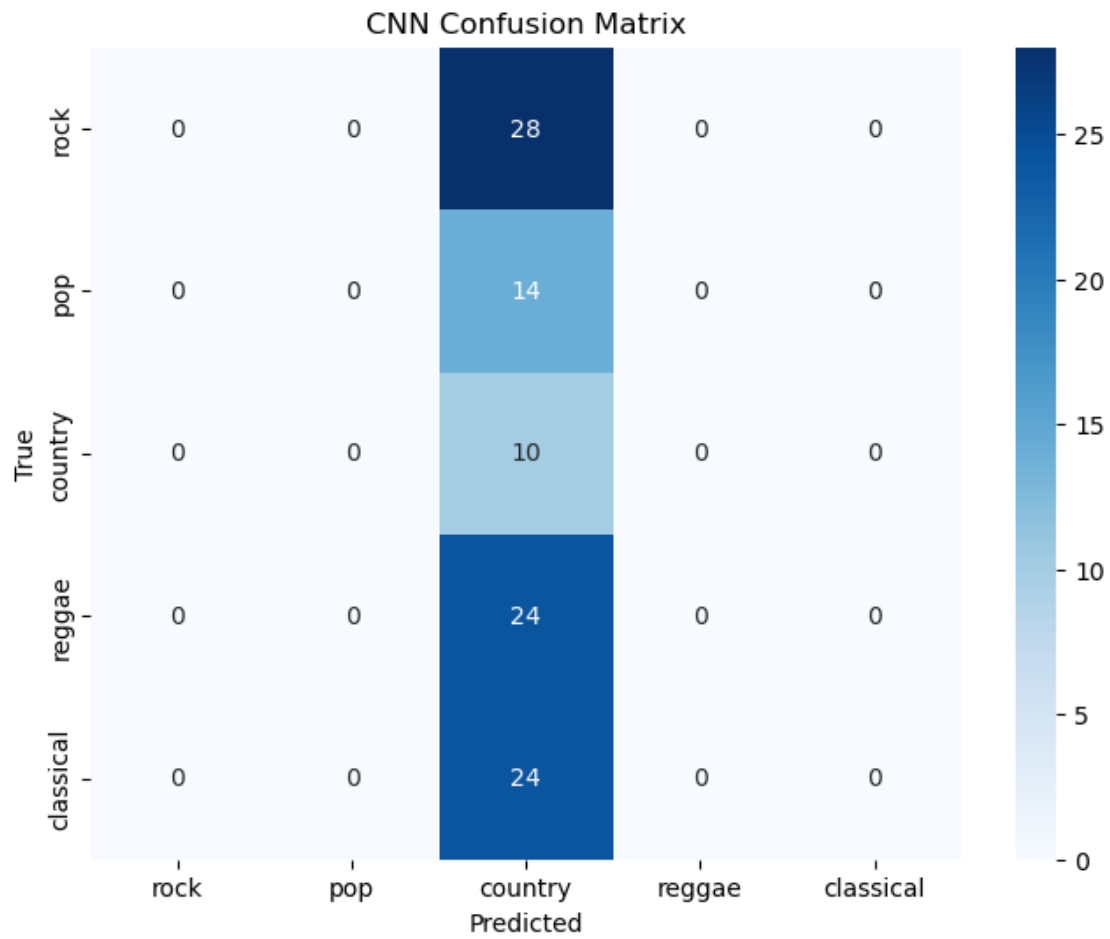
      # Plot the confusion matrix
      plt.figure(figsize=(8, 6))
      sns.heatmap(cnn_cm, annot=True, fmt="d", cmap="Blues", xticklabels=GENRES,
                  yticklabels=GENRES)

```

```
plt.title("CNN Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.show()
```

4/4

0s 99ms/step



[]: