

# Tempogram-Only CNN

March 20, 2025

## 1 CNN for Tempogram

### 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
```

2025-03-20 08:42:01.904114: 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, [256, 256])
image = image.numpy()
```

## 2 3 - Create the model

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

model = models.Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(256, 256, 1)),
```

```

BatchNormalization(),
MaxPooling2D((2, 2)),

Conv2D(64, (3, 3), activation='relu'),
BatchNormalization(),
MaxPooling2D((2, 2)),

Conv2D(128, (3, 3), activation='relu'),
BatchNormalization(),
MaxPooling2D((2, 2)),

Conv2D(256, (3, 3), activation='relu'),
BatchNormalization(),
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, 254, 254, 32)	320
batch_normalization (BatchNormalization)	(None, 254, 254, 32)	128
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0

conv2d_1 (Conv2D)	(None, 125, 125, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 125, 125, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_2 (Conv2D)	(None, 60, 60, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 60, 60, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_3 (Conv2D)	(None, 28, 28, 256)	295,168
batch_normalization_3 (BatchNormalization)	(None, 28, 28, 256)	1,024
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 256)	0
flatten (Flatten)	(None, 50176)	0
dense (Dense)	(None, 512)	25,690,624
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: 26,245,898 (100.12 MB)

Trainable params: 26,244,938 (100.12 MB)

Non-trainable params: 960 (3.75 KB)

### 3 4 - Load the images

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

GENRES = ['blues', 'classical', 'country', 'disco', 'hiphop', 'jazz', 'metal', '
↳ 'pop', 'reggae', 'rock']
FILE_PATH = os.path.join('Data', 'tempograms (30 secs)')
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):
        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, [256, 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])

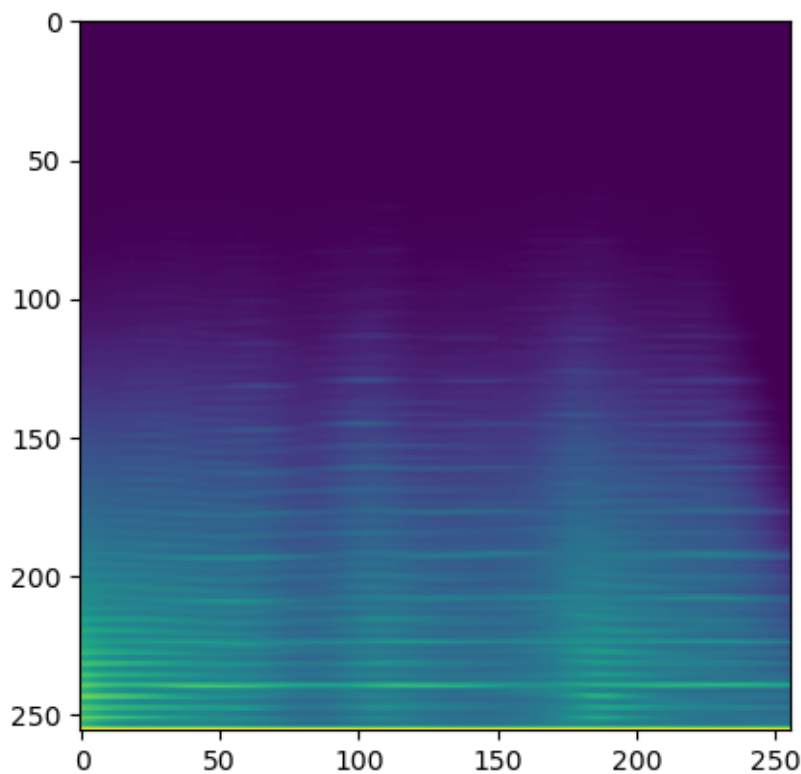
X = np.array(X)
y = np.array(y)

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

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(256, 256))
plt.show()
```



```
[7]: 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)
```

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

```
Epoch 1/20  
25/25          123s 4s/step -  
accuracy: 0.1001 - loss: 4.7744 - val_accuracy: 0.1000 - val_loss: 2.3094 -  
learning_rate: 1.0000e-04  
Epoch 2/20  
25/25          114s 5s/step -  
accuracy: 0.1530 - loss: 2.8332 - val_accuracy: 0.1000 - val_loss: 2.3190 -  
learning_rate: 1.0000e-04  
Epoch 3/20  
25/25          147s 5s/step -  
accuracy: 0.1295 - loss: 2.4556 - val_accuracy: 0.1000 - val_loss: 2.3364 -  
learning_rate: 1.0000e-04  
Epoch 4/20  
25/25          151s 6s/step -  
accuracy: 0.1656 - loss: 2.2950 - val_accuracy: 0.1000 - val_loss: 2.3498 -  
learning_rate: 1.0000e-04  
Epoch 5/20  
25/25          223s 7s/step -  
accuracy: 0.1495 - loss: 2.2987 - val_accuracy: 0.1000 - val_loss: 2.3534 -  
learning_rate: 5.0000e-05  
Epoch 6/20  
25/25          182s 7s/step -  
accuracy: 0.1519 - loss: 2.2809 - val_accuracy: 0.1000 - val_loss: 2.3668 -  
learning_rate: 5.0000e-05  
Epoch 7/20  
25/25          187s 7s/step -  
accuracy: 0.1758 - loss: 2.2086 - val_accuracy: 0.1000 - val_loss: 2.3855 -  
learning_rate: 5.0000e-05  
Epoch 8/20  
25/25          187s 8s/step -  
accuracy: 0.1607 - loss: 2.2146 - val_accuracy: 0.1000 - val_loss: 2.3908 -  
learning_rate: 2.5000e-05  
Epoch 9/20  
25/25          203s 8s/step -  
accuracy: 0.1890 - loss: 2.2048 - val_accuracy: 0.1000 - val_loss: 2.3936 -  
learning_rate: 2.5000e-05  
Epoch 10/20  
25/25          186s 7s/step -  
accuracy: 0.1805 - loss: 2.2220 - val_accuracy: 0.1000 - val_loss: 2.3950 -  
learning_rate: 2.5000e-05  
Epoch 11/20  
25/25          190s 8s/step -  
accuracy: 0.1981 - loss: 2.1543 - val_accuracy: 0.1050 - val_loss: 2.3945 -  
learning_rate: 1.2500e-05  
Epoch 12/20
```

```

25/25          202s 8s/step -
accuracy: 0.1985 - loss: 2.1479 - val_accuracy: 0.1100 - val_loss: 2.3902 -
learning_rate: 1.2500e-05
Epoch 13/20
25/25          206s 8s/step -
accuracy: 0.1788 - loss: 2.1575 - val_accuracy: 0.1200 - val_loss: 2.3780 -
learning_rate: 1.2500e-05
Epoch 14/20
25/25          189s 8s/step -
accuracy: 0.1836 - loss: 2.1996 - val_accuracy: 0.1150 - val_loss: 2.3589 -
learning_rate: 6.2500e-06
Epoch 15/20
25/25          200s 7s/step -
accuracy: 0.1917 - loss: 2.1710 - val_accuracy: 0.0750 - val_loss: 2.3432 -
learning_rate: 6.2500e-06
Epoch 16/20
25/25          204s 8s/step -
accuracy: 0.2209 - loss: 2.1503 - val_accuracy: 0.0700 - val_loss: 2.3255 -
learning_rate: 6.2500e-06
Epoch 17/20
25/25          192s 8s/step -
accuracy: 0.2176 - loss: 2.1260 - val_accuracy: 0.0900 - val_loss: 2.3026 -
learning_rate: 3.1250e-06
Epoch 18/20
25/25          197s 8s/step -
accuracy: 0.2114 - loss: 2.1631 - val_accuracy: 0.1250 - val_loss: 2.2876 -
learning_rate: 3.1250e-06
Epoch 19/20
25/25          203s 8s/step -
accuracy: 0.2408 - loss: 2.1193 - val_accuracy: 0.1200 - val_loss: 2.2749 -
learning_rate: 3.1250e-06
Epoch 20/20
25/25          195s 8s/step -
accuracy: 0.2511 - loss: 2.1153 - val_accuracy: 0.1350 - val_loss: 2.2612 -
learning_rate: 3.1250e-06

```

[8]: <keras.src.callbacks.history.History at 0x7f205046c350>

```

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

```

```

7/7          7s 952ms/step -
accuracy: 0.1310 - loss: 2.2568
Test accuracy: 0.135

```

## 4 Apply the confusion matrix after the model

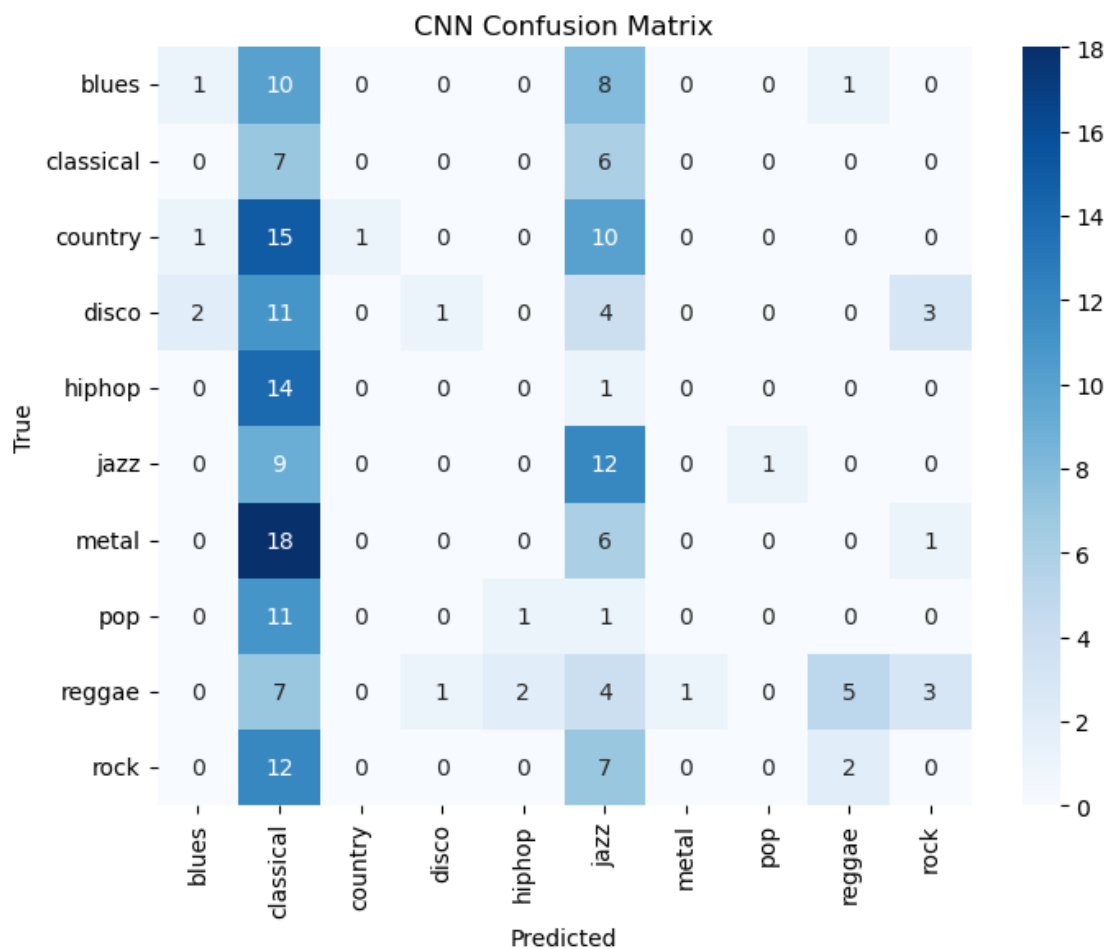
```
[10]: import seaborn as sns
# from sklearn.metrics import confusion
import numpy as NP
from sklearn.metrics import confusion_matrix

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

7s 895ms/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', 'tempograms (30 secs)')
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):
        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, [256, 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])

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(32, (3, 3), activation='relu', input_shape=(256, 256, 1)),
    Normalization(),
    MaxPooling2D((2, 2)),

    Conv2D(64, (3, 3), activation='relu'),
    Normalization(),
    MaxPooling2D((2, 2)),

    Conv2D(128, (3, 3), activation='relu'),
    Normalization(),
    MaxPooling2D((2, 2)),

    Conv2D(256, (3, 3), activation='relu'),
    Normalization(),
    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

```
/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

```
5/5          38s 6s/step -  
accuracy: 0.3451 - loss: 2.2043 - val_accuracy: 0.5250 - val_loss: 1.7436 -  
learning_rate: 1.0000e-04
```

Epoch 2/20

```
5/5          32s 4s/step -  
accuracy: 0.4463 - loss: 1.6111 - val_accuracy: 0.5250 - val_loss: 0.9217 -  
learning_rate: 1.0000e-04
```

Epoch 3/20

```
5/5          27s 5s/step -  
accuracy: 0.5500 - loss: 0.9538 - val_accuracy: 0.4750 - val_loss: 0.7285 -  
learning_rate: 1.0000e-04
```

Epoch 4/20

```
5/5          21s 4s/step -  
accuracy: 0.4806 - loss: 0.9698 - val_accuracy: 0.4750 - val_loss: 0.7707 -  
learning_rate: 1.0000e-04
```

Epoch 5/20

```
5/5          27s 6s/step -  
accuracy: 0.4419 - loss: 1.0288 - val_accuracy: 0.4750 - val_loss: 0.7600 -  
learning_rate: 1.0000e-04
```

Epoch 6/20

```
5/5          38s 5s/step -  
accuracy: 0.5516 - loss: 0.7950 - val_accuracy: 0.4750 - val_loss: 0.7771 -  
learning_rate: 1.0000e-04
```

Epoch 7/20

```
5/5          26s 5s/step -  
accuracy: 0.4775 - loss: 0.8757 - val_accuracy: 0.4750 - val_loss: 0.7772 -  
learning_rate: 5.0000e-05
```

Epoch 8/20

```
5/5          45s 6s/step -  
accuracy: 0.5210 - loss: 0.8222 - val_accuracy: 0.4750 - val_loss: 0.7645 -  
learning_rate: 5.0000e-05
```

Epoch 9/20

```
5/5          34s 5s/step -  
accuracy: 0.5135 - loss: 0.8598 - val_accuracy: 0.4750 - val_loss: 0.7522 -  
learning_rate: 5.0000e-05
```

Epoch 10/20

```
5/5          42s 5s/step -  
accuracy: 0.5135 - loss: 0.8438 - val_accuracy: 0.4750 - val_loss: 0.7454 -  
learning_rate: 2.5000e-05
```

Epoch 11/20  
5/5 23s 5s/step -  
accuracy: 0.5299 - loss: 0.9208 - val\_accuracy: 0.4750 - val\_loss: 0.7442 -  
learning\_rate: 2.5000e-05

Epoch 12/20  
5/5 22s 4s/step -  
accuracy: 0.4938 - loss: 0.8210 - val\_accuracy: 0.4750 - val\_loss: 0.7457 -  
learning\_rate: 2.5000e-05

Epoch 13/20  
5/5 47s 6s/step -  
accuracy: 0.4610 - loss: 0.8990 - val\_accuracy: 0.4750 - val\_loss: 0.7452 -  
learning\_rate: 1.2500e-05

Epoch 14/20  
5/5 40s 6s/step -  
accuracy: 0.5747 - loss: 0.7961 - val\_accuracy: 0.4750 - val\_loss: 0.7452 -  
learning\_rate: 1.2500e-05

Epoch 15/20  
5/5 28s 6s/step -  
accuracy: 0.4355 - loss: 0.9441 - val\_accuracy: 0.4750 - val\_loss: 0.7439 -  
learning\_rate: 1.2500e-05

Epoch 16/20  
5/5 28s 6s/step -  
accuracy: 0.4551 - loss: 0.8932 - val\_accuracy: 0.4750 - val\_loss: 0.7436 -  
learning\_rate: 6.2500e-06

Epoch 17/20  
5/5 28s 6s/step -  
accuracy: 0.5710 - loss: 0.7890 - val\_accuracy: 0.4750 - val\_loss: 0.7436 -  
learning\_rate: 6.2500e-06

Epoch 18/20  
5/5 26s 5s/step -  
accuracy: 0.5205 - loss: 0.8446 - val\_accuracy: 0.4750 - val\_loss: 0.7431 -  
learning\_rate: 6.2500e-06

Epoch 19/20  
5/5 27s 5s/step -  
accuracy: 0.5177 - loss: 0.8032 - val\_accuracy: 0.4750 - val\_loss: 0.7432 -  
learning\_rate: 3.1250e-06

Epoch 20/20  
5/5 24s 5s/step -  
accuracy: 0.4895 - loss: 0.7941 - val\_accuracy: 0.4750 - val\_loss: 0.7429 -  
learning\_rate: 3.1250e-06  
2/2 2s 398ms/step -  
accuracy: 0.4625 - loss: 0.7456  
Test accuracy: 0.475

## 4.2 10 - Confusion Matrix Easy (classical and metal)

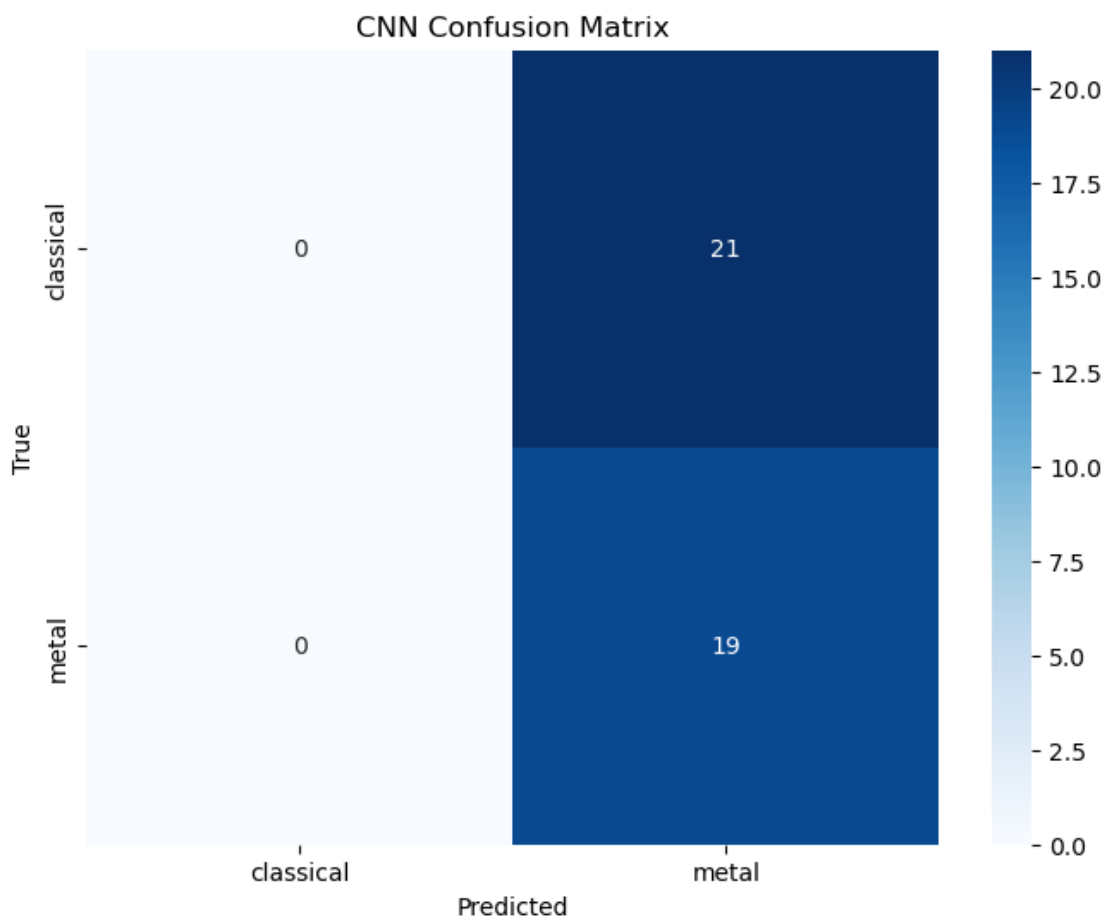
```
[12]: import seaborn as sns
# from sklearn.metrics import confusion
import numpy as NP
from sklearn.metrics import confusion_matrix

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

2s 635ms/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', 'tempograms (30 secs)')
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):
        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, [256, 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])

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(32, (3, 3), activation='relu', input_shape=(256, 256, 1)),
    Normalization(),
    MaxPooling2D((2, 2)),

    Conv2D(64, (3, 3), activation='relu'),
    Normalization(),
    MaxPooling2D((2, 2)),

    Conv2D(128, (3, 3), activation='relu'),
    Normalization(),
    MaxPooling2D((2, 2)),

    Conv2D(256, (3, 3), activation='relu'),
    Normalization(),
    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

```
/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

```
5/5          37s 5s/step -  
accuracy: 0.3098 - loss: 2.1813 - val_accuracy: 0.4750 - val_loss: 1.6631 -  
learning_rate: 1.0000e-04
```

Epoch 2/20

```
5/5          25s 5s/step -  
accuracy: 0.4637 - loss: 1.5099 - val_accuracy: 0.4750 - val_loss: 0.9119 -  
learning_rate: 1.0000e-04
```

Epoch 3/20

```
5/5          25s 5s/step -  
accuracy: 0.5122 - loss: 0.9495 - val_accuracy: 0.4750 - val_loss: 0.7157 -  
learning_rate: 1.0000e-04
```

Epoch 4/20

```
5/5          37s 4s/step -  
accuracy: 0.4688 - loss: 0.9638 - val_accuracy: 0.5250 - val_loss: 0.7386 -  
learning_rate: 1.0000e-04
```

Epoch 5/20

```
5/5          42s 5s/step -  
accuracy: 0.5609 - loss: 0.8824 - val_accuracy: 0.5250 - val_loss: 0.7067 -  
learning_rate: 1.0000e-04
```

Epoch 6/20

```
5/5          23s 5s/step -  
accuracy: 0.5774 - loss: 0.8099 - val_accuracy: 0.4750 - val_loss: 0.7248 -  
learning_rate: 1.0000e-04
```

Epoch 7/20

```
5/5          24s 5s/step -  
accuracy: 0.5084 - loss: 0.8160 - val_accuracy: 0.4750 - val_loss: 0.7539 -  
learning_rate: 1.0000e-04
```

Epoch 8/20

```
5/5          23s 5s/step -  
accuracy: 0.4834 - loss: 0.8989 - val_accuracy: 0.4750 - val_loss: 0.7583 -  
learning_rate: 1.0000e-04
```

Epoch 9/20

```
5/5          23s 5s/step -  
accuracy: 0.5031 - loss: 0.8271 - val_accuracy: 0.4750 - val_loss: 0.7454 -  
learning_rate: 5.0000e-05
```

Epoch 10/20

```
5/5          20s 4s/step -  
accuracy: 0.5009 - loss: 0.8087 - val_accuracy: 0.4750 - val_loss: 0.7282 -  
learning_rate: 5.0000e-05
```



Epoch 11/20  
5/5 24s 5s/step -  
accuracy: 0.4835 - loss: 0.8420 - val\_accuracy: 0.4750 - val\_loss: 0.7196 -  
learning\_rate: 5.0000e-05  
Epoch 12/20  
5/5 26s 5s/step -  
accuracy: 0.4576 - loss: 0.8637 - val\_accuracy: 0.5500 - val\_loss: 0.7177 -  
learning\_rate: 2.5000e-05  
Epoch 13/20  
5/5 23s 5s/step -  
accuracy: 0.5949 - loss: 0.7240 - val\_accuracy: 0.4750 - val\_loss: 0.7143 -  
learning\_rate: 2.5000e-05  
Epoch 14/20  
5/5 43s 5s/step -  
accuracy: 0.4724 - loss: 0.8047 - val\_accuracy: 0.5500 - val\_loss: 0.7115 -  
learning\_rate: 2.5000e-05  
Epoch 15/20  
5/5 39s 5s/step -  
accuracy: 0.4415 - loss: 0.8288 - val\_accuracy: 0.5250 - val\_loss: 0.7110 -  
learning\_rate: 1.2500e-05  
Epoch 16/20  
5/5 24s 5s/step -  
accuracy: 0.4888 - loss: 0.8182 - val\_accuracy: 0.5250 - val\_loss: 0.7104 -  
learning\_rate: 1.2500e-05  
Epoch 17/20  
5/5 41s 5s/step -  
accuracy: 0.4532 - loss: 0.8122 - val\_accuracy: 0.5250 - val\_loss: 0.7101 -  
learning\_rate: 1.2500e-05  
Epoch 18/20  
5/5 23s 5s/step -  
accuracy: 0.4664 - loss: 0.8441 - val\_accuracy: 0.5250 - val\_loss: 0.7103 -  
learning\_rate: 6.2500e-06  
Epoch 19/20  
5/5 21s 4s/step -  
accuracy: 0.4898 - loss: 0.8348 - val\_accuracy: 0.5250 - val\_loss: 0.7105 -  
learning\_rate: 6.2500e-06  
Epoch 20/20  
5/5 42s 5s/step -  
accuracy: 0.5993 - loss: 0.7472 - val\_accuracy: 0.5500 - val\_loss: 0.7102 -  
learning\_rate: 6.2500e-06  
2/2 1s 225ms/step -  
accuracy: 0.5646 - loss: 0.7095  
Test accuracy: 0.550

## 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)

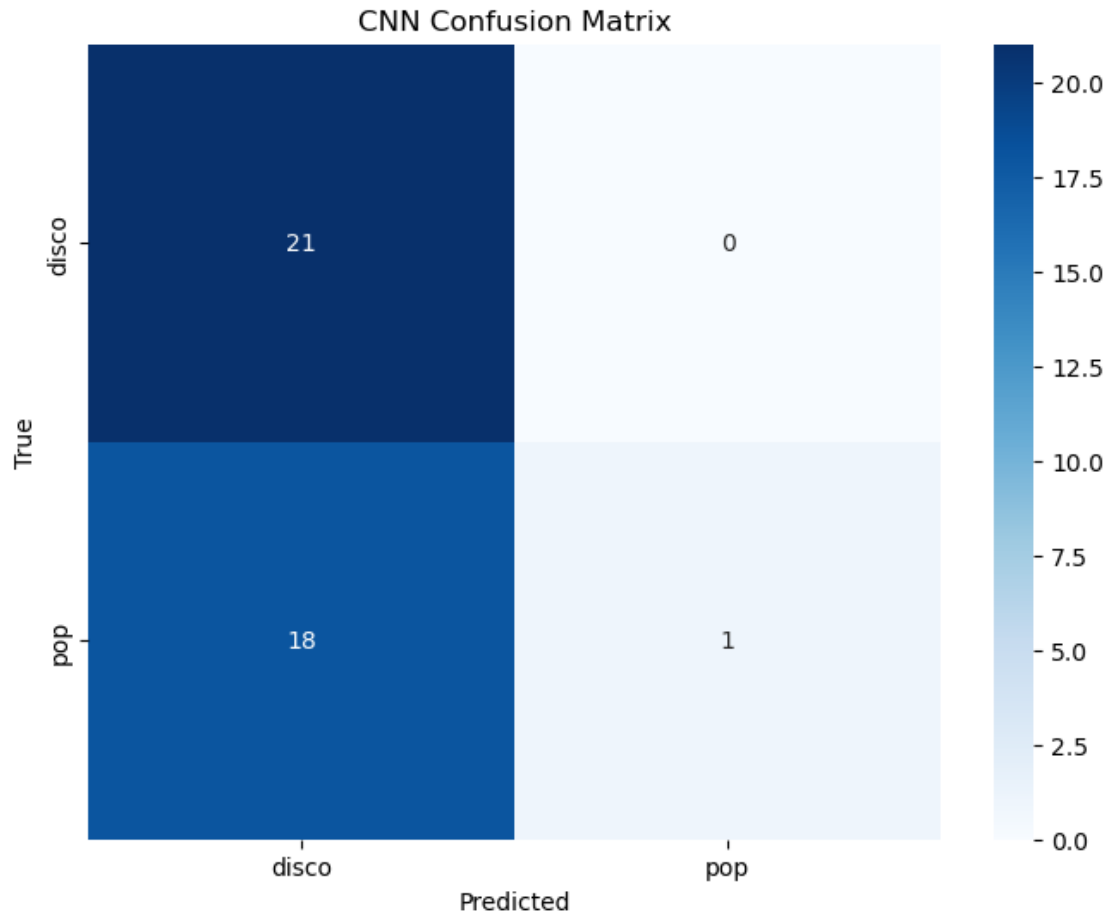
      # Plot the confusion matrix
      plt.figure(figsize=(8, 6))
      sns.heatmap(cnn_cm, annot=True, fmt="d", cmap="Blues", xticklabels=GENRES,
                  yticklabels=GENRES)
      plt.title("CNN Confusion Matrix")
      plt.xlabel("Predicted")
      plt.ylabel("True")
      plt.show()
```

WARNING:tensorflow:5 out of the last 10 calls to <function TensorFlowTrainer.make\_predict\_function.<locals>.one\_step\_on\_data\_distributed at 0x7f1fd436c7c0> 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](https://www.tensorflow.org/guide/function#controlling_retracing) and [https://www.tensorflow.org/api\\_docs/python/tf/function](https://www.tensorflow.org/api_docs/python/tf/function) for more details.

1/2 1s

1s/stepWARNING:tensorflow:6 out of the last 11 calls to <function TensorFlowTrainer.make\_predict\_function.<locals>.one\_step\_on\_data\_distributed at 0x7f1fd436c7c0> 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](https://www.tensorflow.org/guide/function#controlling_retracing) and [https://www.tensorflow.org/api\\_docs/python/tf/function](https://www.tensorflow.org/api_docs/python/tf/function) for more details.

2/2 2s 643ms/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', 'tempograms (30 secs)')
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):
        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, [256, 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])

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(32, (3, 3), activation='relu', input_shape=(256, 256, 1)),
    Normalization(),
    MaxPooling2D((2, 2)),

    Conv2D(64, (3, 3), activation='relu'),
    Normalization(),
    MaxPooling2D((2, 2)),

    Conv2D(128, (3, 3), activation='relu'),
    Normalization(),
    MaxPooling2D((2, 2)),

```

```

Conv2D(256, (3, 3), activation='relu'),
Normalization(),
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', 'disco', 'reggae', 'metal', 'pop']
```

Going through rock

Going through disco

Going through reggae

Going through metal

Going through pop

/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 63s 4s/step -

accuracy: 0.1030 - loss: 2.2777 - val\_accuracy: 0.1000 - val\_loss: 2.1451 -

learning\_rate: 1.0000e-04

Epoch 2/20  
13/13 83s 4s/step -  
accuracy: 0.2136 - loss: 2.0416 - val\_accuracy: 0.1000 - val\_loss: 1.9178 -  
learning\_rate: 1.0000e-04

Epoch 3/20  
13/13 81s 4s/step -  
accuracy: 0.2196 - loss: 1.9410 - val\_accuracy: 0.1400 - val\_loss: 1.8166 -  
learning\_rate: 1.0000e-04

Epoch 4/20  
13/13 80s 4s/step -  
accuracy: 0.2595 - loss: 1.8321 - val\_accuracy: 0.1400 - val\_loss: 1.7923 -  
learning\_rate: 1.0000e-04

Epoch 5/20  
13/13 53s 4s/step -  
accuracy: 0.2032 - loss: 1.8528 - val\_accuracy: 0.1400 - val\_loss: 1.7592 -  
learning\_rate: 1.0000e-04

Epoch 6/20  
13/13 51s 4s/step -  
accuracy: 0.1810 - loss: 1.8780 - val\_accuracy: 0.1400 - val\_loss: 1.7554 -  
learning\_rate: 1.0000e-04

Epoch 7/20  
13/13 52s 4s/step -  
accuracy: 0.2131 - loss: 1.8251 - val\_accuracy: 0.1400 - val\_loss: 1.7576 -  
learning\_rate: 1.0000e-04

Epoch 8/20  
13/13 81s 4s/step -  
accuracy: 0.2358 - loss: 1.7375 - val\_accuracy: 0.1400 - val\_loss: 1.7339 -  
learning\_rate: 1.0000e-04

Epoch 9/20  
13/13 47s 4s/step -  
accuracy: 0.2150 - loss: 1.7343 - val\_accuracy: 0.1400 - val\_loss: 1.7638 -  
learning\_rate: 1.0000e-04

Epoch 10/20  
13/13 49s 4s/step -  
accuracy: 0.1877 - loss: 1.7438 - val\_accuracy: 0.1400 - val\_loss: 1.7687 -  
learning\_rate: 1.0000e-04

Epoch 11/20  
13/13 48s 4s/step -  
accuracy: 0.2219 - loss: 1.7560 - val\_accuracy: 0.1400 - val\_loss: 1.6918 -  
learning\_rate: 1.0000e-04

Epoch 12/20  
13/13 79s 3s/step -  
accuracy: 0.1943 - loss: 1.7281 - val\_accuracy: 0.1400 - val\_loss: 1.6797 -  
learning\_rate: 1.0000e-04

Epoch 13/20  
13/13 47s 4s/step -  
accuracy: 0.2269 - loss: 1.6970 - val\_accuracy: 0.1600 - val\_loss: 1.6660 -  
learning\_rate: 1.0000e-04

```

Epoch 14/20
13/13          47s 4s/step -
accuracy: 0.2614 - loss: 1.6811 - val_accuracy: 0.3000 - val_loss: 1.6239 -
learning_rate: 1.0000e-04
Epoch 15/20
13/13          47s 4s/step -
accuracy: 0.2378 - loss: 1.6758 - val_accuracy: 0.2900 - val_loss: 1.6162 -
learning_rate: 1.0000e-04
Epoch 16/20
13/13          36s 3s/step -
accuracy: 0.2947 - loss: 1.5697 - val_accuracy: 0.3000 - val_loss: 1.5655 -
learning_rate: 1.0000e-04
Epoch 17/20
13/13          50s 4s/step -
accuracy: 0.3339 - loss: 1.5470 - val_accuracy: 0.3100 - val_loss: 1.5617 -
learning_rate: 1.0000e-04
Epoch 18/20
13/13          77s 3s/step -
accuracy: 0.2929 - loss: 1.5705 - val_accuracy: 0.3200 - val_loss: 1.5785 -
learning_rate: 1.0000e-04
Epoch 19/20
13/13          41s 3s/step -
accuracy: 0.3028 - loss: 1.5406 - val_accuracy: 0.3100 - val_loss: 1.5470 -
learning_rate: 1.0000e-04
Epoch 20/20
13/13          93s 4s/step -
accuracy: 0.3113 - loss: 1.5715 - val_accuracy: 0.3000 - val_loss: 1.6595 -
learning_rate: 1.0000e-04
4/4           3s 601ms/step -
accuracy: 0.3075 - loss: 1.6741
Test accuracy: 0.300

```

#### 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)

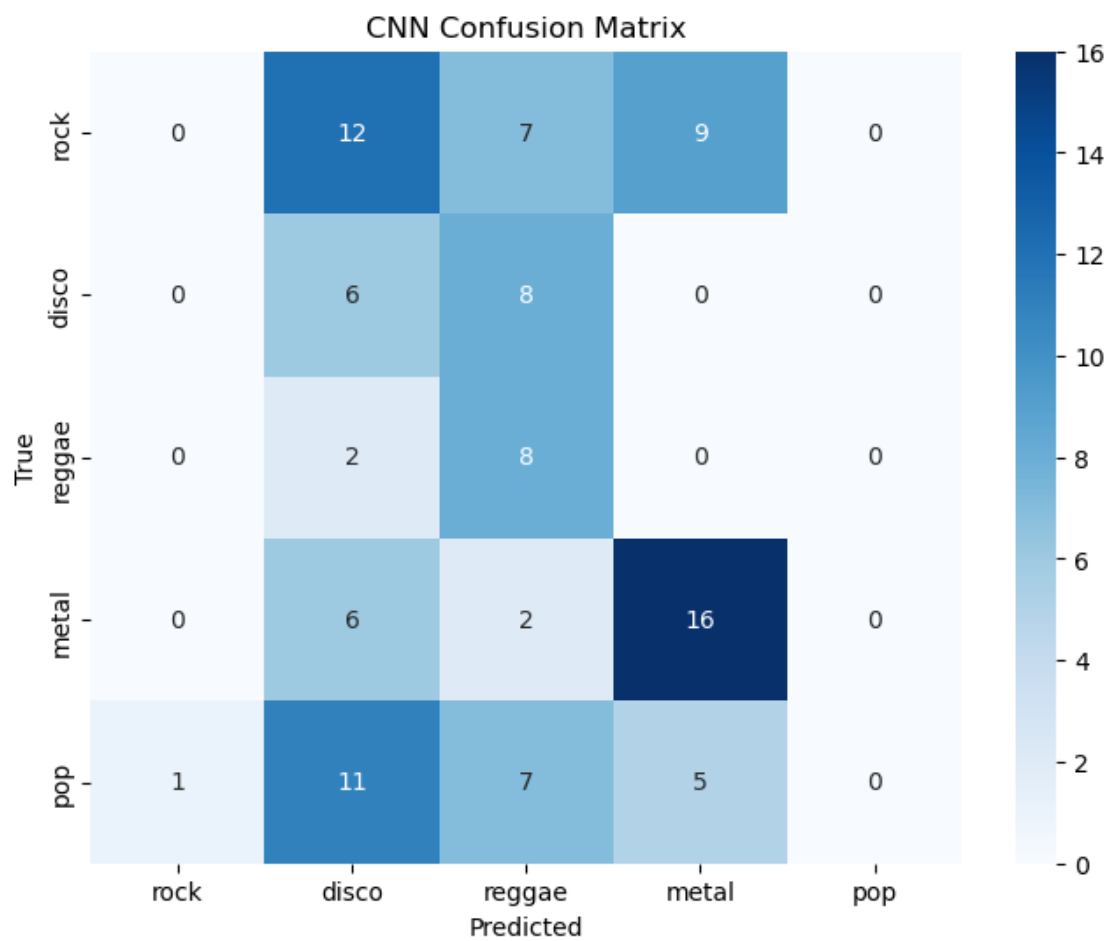
      # Plot the confusion matrix
      plt.figure(figsize=(8, 6))
      sns.heatmap(cnn_cm, annot=True, fmt="d", cmap="Blues", xticklabels=GENRES,
                  yticklabels=GENRES)
      plt.title("CNN Confusion Matrix")

```

```
plt.xlabel("Predicted")
plt.ylabel("True")
plt.show()
```

4/4

3s 620ms/step



[ ]: