CNN for Chromagram only

1 - All 10

In [2]:

```
import os
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from tensorflow.keras import models
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ReduceLROnPlateau
import matplotlib.pyplot as plt

# 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

# Define the genres and file paths
GENRES = ['blues', 'classical', 'country', 'disco', 'hiphop', 'jazz', 'metal', 'pop', 'reggae', 'rock']
FILE_PATH = os.path.join('Data', 'chromagrams', 'chromagram_12')

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

# Organize data by song ID
song_to_clips = {}

for genre in GENRES:
    genre_dir = os.path.join(FILE_PATH, genre)
    print(f"Processing genre: {genre}")
    for file in os.listdir(genre_dir):
        if not file.endswith(".png"):
            continue

        song_id = file.split("_clip_")[0]  # Extract song ID (e.g., "blues.00042")

        if song_id not in song_to_clips:
            song_to_clips[song_id] = []

        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])  # Resize to 256x256
        image = augment_image(image)  # Apply augmentation
        image = image.numpy()  # Convert to numpy array

        song_to_clips[song_id].append((image, GENRE_TO_INDEX[genre]))

# Convert dictionary to list format
song_ids = list(song_to_clips.keys())
train_ids, test_ids = train_test_split(song_ids, test_size=0.2, random_state=42)

X_train, y_train, X_test, y_test = [], [], [], []

# Assign clips based on the train-test split
for song_id in song_ids:
    clips = song_to_clips[song_id]
    if song_id in train_ids:
        for image, label in clips:
            X_train.append(image)
            y_train.append(label)
    else:
        for image, label in clips:
            X_test.append(image)
            y_test.append(label)

# Convert to numpy arrays
X_train = np.array(X_train)
y_train = np.array(y_train)
X_test = np.array(X_test)
y_test = np.array(y_test)
```

```python
print(f"Train set: {len(X_train)} samples")
print(f"Test set: {len(X_test)} samples")

# Define the CNN model
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')
])

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.0001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Learning rate adjustment
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3, min_lr=1e-6)

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

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

```
Processing genre: blues
Processing genre: classical
Processing genre: country
Processing genre: disco
Processing genre: hiphop
Processing genre: jazz
Processing genre: metal
Processing genre: pop
Processing genre: reggae
Processing genre: rock
Train set: 800 samples
Test set: 200 samples
```

```
/Users/conorwoollatt/.pyenv/versions/3.9.6/lib/python3.9/site-packages/keras/src/layers/convolutional/base_conv.py:1
07: 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
25/25 ━━━━━━━━━━━━━━━━━━━━ 8s 267ms/step - accuracy: 0.0969 - loss: 2.5299 - val_accuracy: 0.0750 - val_loss: 2.3263
- learning_rate: 1.0000e-04
Epoch 2/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 10s 272ms/step - accuracy: 0.0740 - loss: 2.4057 - val_accuracy: 0.0650 - val_loss: 2.312
4 - learning_rate: 1.0000e-04
Epoch 3/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 10s 270ms/step - accuracy: 0.0907 - loss: 2.3260 - val_accuracy: 0.0750 - val_loss: 2.309
5 - learning_rate: 1.0000e-04
Epoch 4/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 288ms/step - accuracy: 0.1164 - loss: 2.3113 - val_accuracy: 0.0650 - val_loss: 2.3035
- learning_rate: 1.0000e-04
Epoch 5/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 10s 261ms/step - accuracy: 0.1200 - loss: 2.2998 - val_accuracy: 0.0700 - val_loss: 2.306
1 - learning_rate: 1.0000e-04
Epoch 6/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 276ms/step - accuracy: 0.0917 - loss: 2.3100 - val_accuracy: 0.1050 - val_loss: 2.3030
- learning_rate: 1.0000e-04
Epoch 7/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 270ms/step - accuracy: 0.0839 - loss: 2.3032 - val_accuracy: 0.0650 - val_loss: 2.3045
- learning_rate: 1.0000e-04
Epoch 8/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 6s 245ms/step - accuracy: 0.1043 - loss: 2.3042 - val_accuracy: 0.1050 - val_loss: 2.3023
- learning_rate: 1.0000e-04
Epoch 9/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 264ms/step - accuracy: 0.1130 - loss: 2.2999 - val_accuracy: 0.0650 - val_loss: 2.3039
- learning_rate: 1.0000e-04
Epoch 10/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 273ms/step - accuracy: 0.1188 - loss: 2.3021 - val_accuracy: 0.0650 - val_loss: 2.3041
- learning_rate: 1.0000e-04
Epoch 11/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 264ms/step - accuracy: 0.0931 - loss: 2.3027 - val_accuracy: 0.0650 - val_loss: 2.3043
- learning_rate: 1.0000e-04
Epoch 12/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 6s 256ms/step - accuracy: 0.1269 - loss: 2.3023 - val_accuracy: 0.0650 - val_loss: 2.3044
- learning_rate: 5.0000e-05
Epoch 13/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 273ms/step - accuracy: 0.1146 - loss: 2.3018 - val_accuracy: 0.0650 - val_loss: 2.3044
- learning_rate: 5.0000e-05
Epoch 14/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 270ms/step - accuracy: 0.1170 - loss: 2.3022 - val_accuracy: 0.0650 - val_loss: 2.3045
- learning_rate: 5.0000e-05
Epoch 15/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 271ms/step - accuracy: 0.1063 - loss: 2.3019 - val_accuracy: 0.0650 - val_loss: 2.3046
- learning_rate: 2.5000e-05
Epoch 16/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 6s 261ms/step - accuracy: 0.1142 - loss: 2.3017 - val_accuracy: 0.0650 - val_loss: 2.3046
- learning_rate: 2.5000e-05
Epoch 17/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 277ms/step - accuracy: 0.1106 - loss: 2.3020 - val_accuracy: 0.0650 - val_loss: 2.3047
- learning_rate: 2.5000e-05
Epoch 18/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 6s 256ms/step - accuracy: 0.1046 - loss: 2.3023 - val_accuracy: 0.0650 - val_loss: 2.3047
- learning_rate: 1.2500e-05
Epoch 19/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 275ms/step - accuracy: 0.1052 - loss: 2.3024 - val_accuracy: 0.0650 - val_loss: 2.3047
- learning_rate: 1.2500e-05
Epoch 20/20
25/25 ━━━━━━━━━━━━━━━━━━━━ 7s 269ms/step - accuracy: 0.1097 - loss: 2.3024 - val_accuracy: 0.0650 - val_loss: 2.3047
- learning_rate: 1.2500e-05
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 71ms/step - accuracy: 0.0349 - loss: 2.3046
Test accuracy: 0.065
```

Apply the confusion matrix after the model

In [3]:

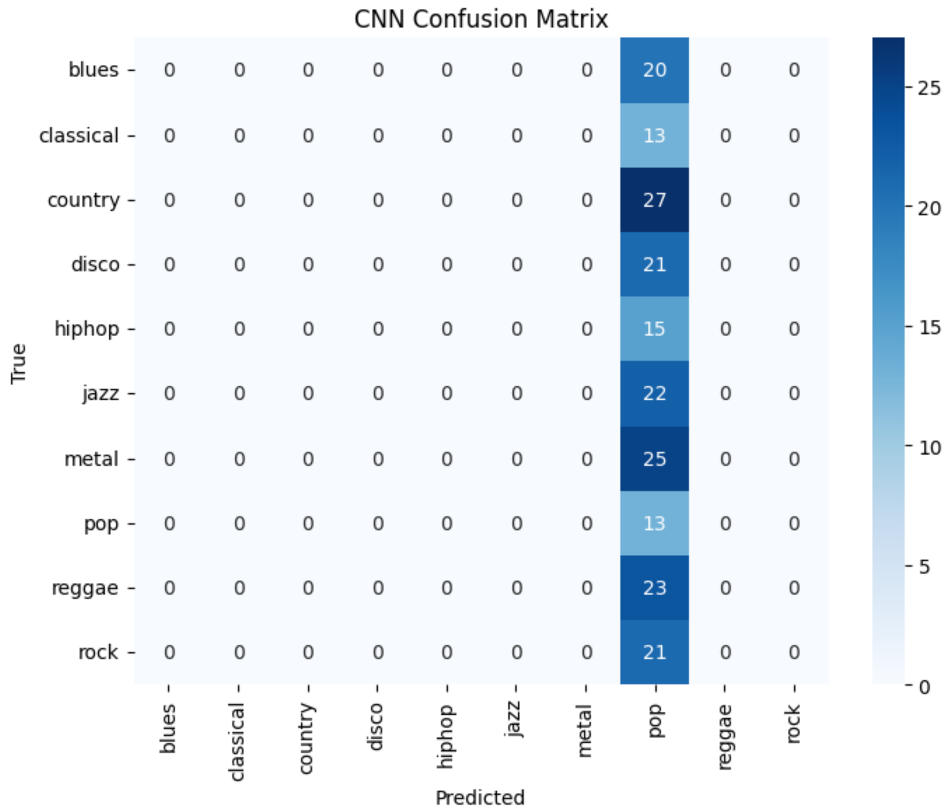
```python
import seaborn as sns
# from sklearn.metrics import confusion
import numpy as NP
from sklearn.metrics import confusion_matrix

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 ━━━━━━━━━━━━━━━━━━━━ 1s 64ms/step



2 - Limited Genres Easy (metal and classical)

In [4]:
```
import os
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from tensorflow.keras import models
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ReduceLROnPlateau
import matplotlib.pyplot as plt

# 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

# Define the genres and file paths
GENRES = ['classical', 'metal']
FILE_PATH = os.path.join('Data', 'chromagrams', 'chromagram_12')

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

# Organize data by song ID
song_to_clips = {}

for genre in GENRES:
    genre_dir = os.path.join(FILE_PATH, genre)
    print(f"Processing genre: {genre}")
    for file in os.listdir(genre_dir):
        if not file.endswith(".png"):
            continue

        song_id = file.split("_clip_")[0]  # Extract song ID (e.g., "blues.00042")

        if song_id not in song_to_clips:
            song_to_clips[song_id] = []
```

```
        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])  # Resize to 256x256
        image = augment_image(image)  # Apply augmentation
        image = image.numpy()  # Convert to numpy array

        song_to_clips[song_id].append((image, GENRE_TO_INDEX[genre]))

# Convert dictionary to list format
song_ids = list(song_to_clips.keys())
train_ids, test_ids = train_test_split(song_ids, test_size=0.2, random_state=42)

X_train, y_train, X_test, y_test = [], [], [], []

# Assign clips based on the train-test split
for song_id in song_ids:
    clips = song_to_clips[song_id]
    if song_id in train_ids:
        for image, label in clips:
            X_train.append(image)
            y_train.append(label)
    else:
        for image, label in clips:
            X_test.append(image)
            y_test.append(label)

# Convert to numpy arrays
X_train = np.array(X_train)
y_train = np.array(y_train)
X_test = np.array(X_test)
y_test = np.array(y_test)

print(f"Train set: {len(X_train)} samples")
print(f"Test set: {len(X_test)} samples")

# Define the CNN model
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')
])

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.0001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Learning rate adjustment
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3, min_lr=1e-6)

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

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

```
Processing genre: classical
Processing genre: metal
Train set: 160 samples
Test set: 40 samples
```

```
/Users/conorwoollatt/.pyenv/versions/3.9.6/lib/python3.9/site-packages/keras/src/layers/convolutional/base_conv.py:1
07: 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 ━━━━━━━━━━━━━━━━━━━━ 2s 326ms/step - accuracy: 0.2608 - loss: 1.7812 - val_accuracy: 0.5250 - val_loss: 0.7262 -
learning_rate: 1.0000e-04
Epoch 2/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 291ms/step - accuracy: 0.5343 - loss: 1.0690 - val_accuracy: 0.4750 - val_loss: 0.7515 -
learning_rate: 1.0000e-04
Epoch 3/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 323ms/step - accuracy: 0.4437 - loss: 1.1460 - val_accuracy: 0.5250 - val_loss: 0.6929 -
learning_rate: 1.0000e-04
Epoch 4/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 281ms/step - accuracy: 0.4233 - loss: 1.3310 - val_accuracy: 0.6750 - val_loss: 0.7005 -
learning_rate: 1.0000e-04
Epoch 5/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 269ms/step - accuracy: 0.4762 - loss: 1.0545 - val_accuracy: 0.5250 - val_loss: 0.7120 -
learning_rate: 1.0000e-04
Epoch 6/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 3s 298ms/step - accuracy: 0.4110 - loss: 1.1116 - val_accuracy: 0.6750 - val_loss: 0.7428 -
learning_rate: 1.0000e-04
Epoch 7/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 268ms/step - accuracy: 0.4583 - loss: 1.1160 - val_accuracy: 0.4750 - val_loss: 0.7668 -
learning_rate: 5.0000e-05
Epoch 8/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 305ms/step - accuracy: 0.4920 - loss: 0.9913 - val_accuracy: 0.4750 - val_loss: 0.8066 -
learning_rate: 5.0000e-05
Epoch 9/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 282ms/step - accuracy: 0.5559 - loss: 0.9169 - val_accuracy: 0.4750 - val_loss: 0.7706 -
learning_rate: 5.0000e-05
Epoch 10/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 284ms/step - accuracy: 0.5348 - loss: 0.8779 - val_accuracy: 0.4750 - val_loss: 0.7460 -
learning_rate: 2.5000e-05
Epoch 11/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 294ms/step - accuracy: 0.4830 - loss: 0.9666 - val_accuracy: 0.5250 - val_loss: 0.7317 -
learning_rate: 2.5000e-05
Epoch 12/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 286ms/step - accuracy: 0.5378 - loss: 0.9007 - val_accuracy: 0.5250 - val_loss: 0.7289 -
learning_rate: 2.5000e-05
Epoch 13/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 283ms/step - accuracy: 0.5048 - loss: 0.9938 - val_accuracy: 0.5000 - val_loss: 0.7319 -
learning_rate: 1.2500e-05
Epoch 14/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 269ms/step - accuracy: 0.5135 - loss: 0.8181 - val_accuracy: 0.4750 - val_loss: 0.7341 -
learning_rate: 1.2500e-05
Epoch 15/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 260ms/step - accuracy: 0.4701 - loss: 0.9237 - val_accuracy: 0.4750 - val_loss: 0.7379 -
learning_rate: 1.2500e-05
Epoch 16/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 298ms/step - accuracy: 0.4623 - loss: 0.9736 - val_accuracy: 0.4750 - val_loss: 0.7366 -
learning_rate: 6.2500e-06
Epoch 17/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 252ms/step - accuracy: 0.5218 - loss: 0.8828 - val_accuracy: 0.5000 - val_loss: 0.7327 -
learning_rate: 6.2500e-06
Epoch 18/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 283ms/step - accuracy: 0.5305 - loss: 0.9110 - val_accuracy: 0.5000 - val_loss: 0.7294 -
learning_rate: 6.2500e-06
Epoch 19/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 258ms/step - accuracy: 0.5420 - loss: 0.8423 - val_accuracy: 0.5000 - val_loss: 0.7272 -
learning_rate: 3.1250e-06
Epoch 20/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 246ms/step - accuracy: 0.5529 - loss: 0.8138 - val_accuracy: 0.5250 - val_loss: 0.7257 -
learning_rate: 3.1250e-06
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - accuracy: 0.4854 - loss: 0.7325
Test accuracy: 0.525
```

Confusion Matrix Easy (classical and metal)

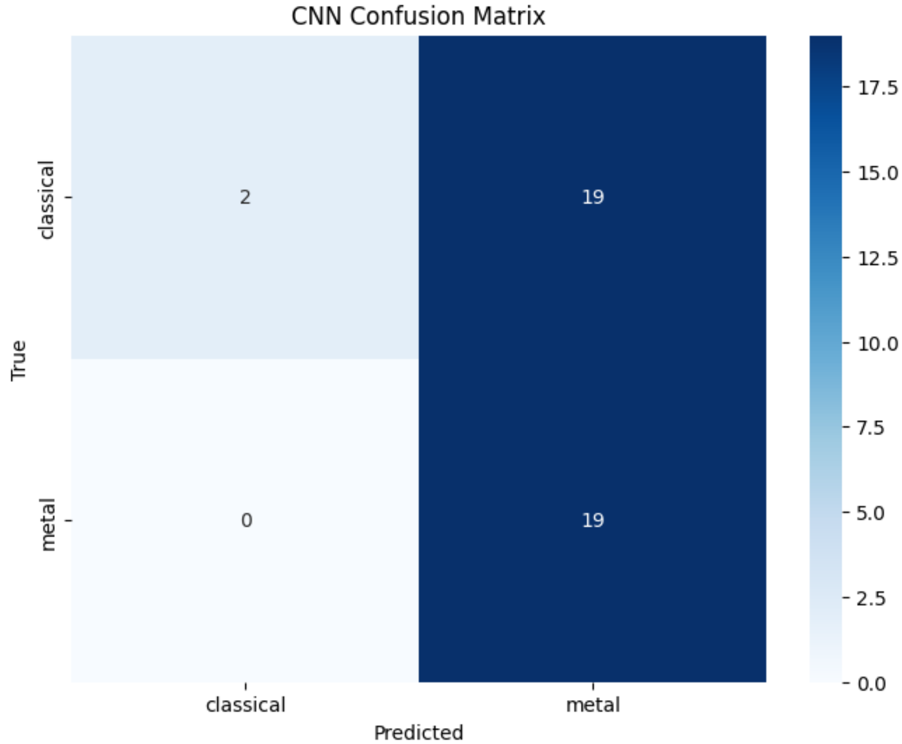
In [5]:
```python
import seaborn as sns
# from sklearn.metrics import confusion
import numpy as NP
from sklearn.metrics import confusion_matrix

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 256ms/step
```



3 - Limited genres Hard (disco and pop)

In [6]:
```
import os
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from tensorflow.keras import models
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ReduceLROnPlateau
import matplotlib.pyplot as plt

# 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

# Define the genres and file paths
GENRES = ['disco', 'pop']
FILE_PATH = os.path.join('Data', 'chromagrams', 'chromagram_12')

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

# Organize data by song ID
song_to_clips = {}

for genre in GENRES:
    genre_dir = os.path.join(FILE_PATH, genre)
    print(f"Processing genre: {genre}")
    for file in os.listdir(genre_dir):
        if not file.endswith(".png"):
            continue

        song_id = file.split("_clip_")[0]  # Extract song ID (e.g., "blues.00042")

        if song_id not in song_to_clips:
            song_to_clips[song_id] = []

        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])  # Resize to 256x256
        image = augment_image(image)  # Apply augmentation
        image = image.numpy()  # Convert to numpy array

        song_to_clips[song_id].append((image, GENRE_TO_INDEX[genre]))

# Convert dictionary to list format
song_ids = list(song_to_clips.keys())
train_ids, test_ids = train_test_split(song_ids, test_size=0.2, random_state=42)

X_train, y_train, X_test, y_test = [], [], [], []

# Assign clips based on the train-test split
for song_id in song_ids:
    clips = song_to_clips[song_id]
    if song_id in train_ids:
        for image, label in clips:
            X_train.append(image)
            y_train.append(label)
    else:
        for image, label in clips:
            X_test.append(image)
            y_test.append(label)

# Convert to numpy arrays
X_train = np.array(X_train)
y_train = np.array(y_train)
X_test = np.array(X_test)
y_test = np.array(y_test)

print(f"Train set: {len(X_train)} samples")
print(f"Test set: {len(X_test)} samples")

# Define the CNN model
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')
])

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.0001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Learning rate adjustment
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3, min_lr=1e-6)

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

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

```
Processing genre: disco
Processing genre: pop
Train set: 160 samples
Test set: 40 samples
Epoch 1/20
```

```
/Users/conorwoollatt/.pyenv/versions/3.9.6/lib/python3.9/site-packages/keras/src/layers/convolutional/base_conv.py:1
07: 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 345ms/step - accuracy: 0.3882 - loss: 1.5773 - val_accuracy: 0.4750 - val_loss: 0.7477 -
learning_rate: 1.0000e-04
Epoch 2/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 265ms/step - accuracy: 0.5155 - loss: 1.1924 - val_accuracy: 0.5250 - val_loss: 0.7627 -
learning_rate: 1.0000e-04
Epoch 3/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 267ms/step - accuracy: 0.4023 - loss: 1.4256 - val_accuracy: 0.5250 - val_loss: 0.7319 -
learning_rate: 1.0000e-04
Epoch 4/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 293ms/step - accuracy: 0.5408 - loss: 1.0960 - val_accuracy: 0.6000 - val_loss: 0.6931 -
learning_rate: 1.0000e-04
Epoch 5/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 323ms/step - accuracy: 0.5230 - loss: 1.1351 - val_accuracy: 0.5000 - val_loss: 0.7002 -
learning_rate: 1.0000e-04
Epoch 6/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 322ms/step - accuracy: 0.5539 - loss: 0.9147 - val_accuracy: 0.5000 - val_loss: 0.7030 -
learning_rate: 1.0000e-04
Epoch 7/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 293ms/step - accuracy: 0.5174 - loss: 0.9118 - val_accuracy: 0.5250 - val_loss: 0.7014 -
learning_rate: 1.0000e-04
Epoch 8/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 321ms/step - accuracy: 0.5295 - loss: 0.9475 - val_accuracy: 0.5250 - val_loss: 0.7269 -
learning_rate: 5.0000e-05
Epoch 9/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 324ms/step - accuracy: 0.4847 - loss: 0.9969 - val_accuracy: 0.5250 - val_loss: 0.7346 -
learning_rate: 5.0000e-05
Epoch 10/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 250ms/step - accuracy: 0.4896 - loss: 0.9549 - val_accuracy: 0.5250 - val_loss: 0.7207 -
learning_rate: 5.0000e-05
Epoch 11/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 261ms/step - accuracy: 0.5505 - loss: 0.8523 - val_accuracy: 0.5250 - val_loss: 0.7135 -
learning_rate: 2.5000e-05
Epoch 12/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 300ms/step - accuracy: 0.3615 - loss: 1.0449 - val_accuracy: 0.5250 - val_loss: 0.7139 -
learning_rate: 2.5000e-05
Epoch 13/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 228ms/step - accuracy: 0.5458 - loss: 0.8602 - val_accuracy: 0.5250 - val_loss: 0.7131 -
learning_rate: 2.5000e-05
Epoch 14/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 241ms/step - accuracy: 0.6007 - loss: 0.8236 - val_accuracy: 0.5250 - val_loss: 0.7136 -
learning_rate: 1.2500e-05
Epoch 15/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 230ms/step - accuracy: 0.5156 - loss: 0.8184 - val_accuracy: 0.5250 - val_loss: 0.7139 -
learning_rate: 1.2500e-05
Epoch 16/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 229ms/step - accuracy: 0.4886 - loss: 0.9472 - val_accuracy: 0.5250 - val_loss: 0.7139 -
learning_rate: 1.2500e-05
Epoch 17/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 235ms/step - accuracy: 0.5069 - loss: 0.9268 - val_accuracy: 0.5250 - val_loss: 0.7141 -
learning_rate: 6.2500e-06
Epoch 18/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 221ms/step - accuracy: 0.4649 - loss: 0.9376 - val_accuracy: 0.5250 - val_loss: 0.7147 -
learning_rate: 6.2500e-06
Epoch 19/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 219ms/step - accuracy: 0.5282 - loss: 0.9528 - val_accuracy: 0.5250 - val_loss: 0.7148 -
learning_rate: 6.2500e-06
Epoch 20/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 226ms/step - accuracy: 0.5541 - loss: 0.8524 - val_accuracy: 0.5250 - val_loss: 0.7149 -
learning_rate: 3.1250e-06
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 0.5687 - loss: 0.7040
Test accuracy: 0.525
```

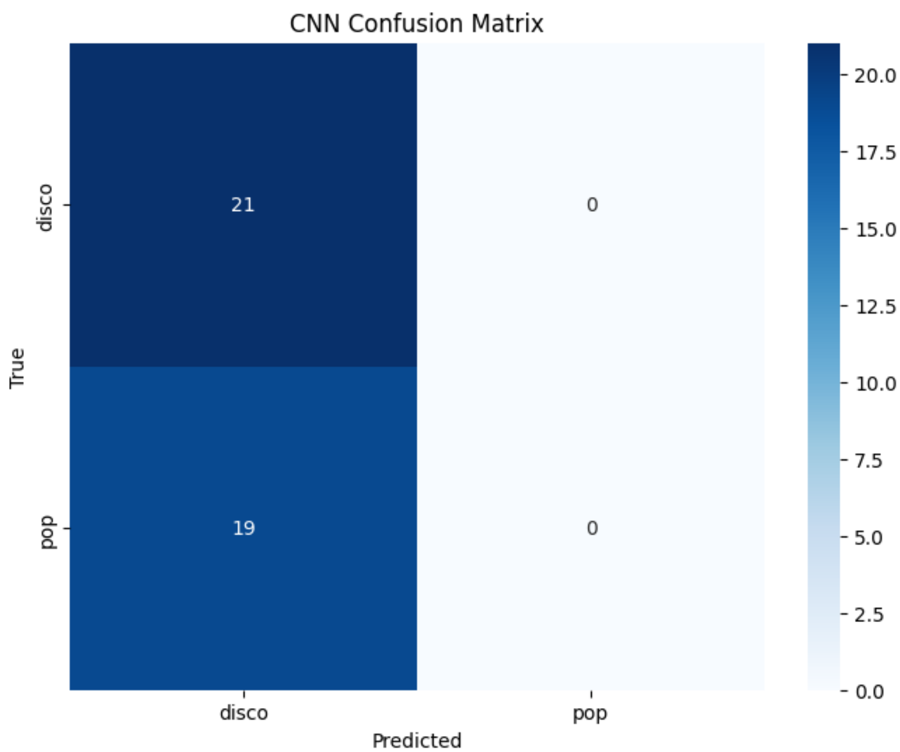
12 - Confusion Matrix Hard (disco and pop)

In [7]:
```
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 0x3aaf84940> 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 81ms/stepWARNING:tensorflow:6 out of the last 11 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x3aaf84940> 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 115ms/step
```



13 - Limited Genres Medium (5 random)

In [8]:
```
import os
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from tensorflow.keras import models
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ReduceLROnPlateau
import matplotlib.pyplot as plt
import random

# Augmentation function
```

```python
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

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_12')

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

# Organize data by song ID
song_to_clips = {}

for genre in GENRES:
    genre_dir = os.path.join(FILE_PATH, genre)
    print(f"Processing genre: {genre}")
    for file in os.listdir(genre_dir):
        if not file.endswith(".png"):
            continue

        song_id = file.split("_clip_")[0]  # Extract song ID (e.g., "blues.00042")

        if song_id not in song_to_clips:
            song_to_clips[song_id] = []

        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])  # Resize to 256x256
        image = augment_image(image)  # Apply augmentation
        image = image.numpy()  # Convert to numpy array

        song_to_clips[song_id].append((image, GENRE_TO_INDEX[genre]))

# Convert dictionary to list format
song_ids = list(song_to_clips.keys())
train_ids, test_ids = train_test_split(song_ids, test_size=0.2, random_state=42)

X_train, y_train, X_test, y_test = [], [], [], []

# Assign clips based on the train-test split
for song_id in song_ids:
    clips = song_to_clips[song_id]
    if song_id in train_ids:
        for image, label in clips:
            X_train.append(image)
            y_train.append(label)
    else:
        for image, label in clips:
            X_test.append(image)
            y_test.append(label)

# Convert to numpy arrays
X_train = np.array(X_train)
y_train = np.array(y_train)
X_test = np.array(X_test)
y_test = np.array(y_test)

print(f"Train set: {len(X_train)} samples")
print(f"Test set: {len(X_test)} samples")

# Define the CNN model
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')
])
```

```
# Compile the model
model.compile(optimizer=Adam(learning_rate=0.0001), loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Learning rate adjustment
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3, min_lr=1e-6)

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

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

```
['reggae', 'country', 'blues', 'classical', 'metal']
Processing genre: reggae
Processing genre: country
Processing genre: blues
Processing genre: classical
Processing genre: metal
Train set: 400 samples
Test set: 100 samples
```

```
/Users/conorwoollatt/.pyenv/versions/3.9.6/lib/python3.9/site-packages/keras/src/layers/convolutional/base_conv.py:1
07: 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 ━━━━━━━━━━━━━━━━━━━━ 6s 285ms/step - accuracy: 0.1485 - loss: 2.1901 - val_accuracy: 0.1500 - val_loss: 1.9326
- learning_rate: 1.0000e-04
Epoch 2/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 266ms/step - accuracy: 0.1975 - loss: 2.0556 - val_accuracy: 0.1400 - val_loss: 1.8337
- learning_rate: 1.0000e-04
Epoch 3/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 250ms/step - accuracy: 0.2215 - loss: 1.9586 - val_accuracy: 0.1400 - val_loss: 1.8081
- learning_rate: 1.0000e-04
Epoch 4/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 4s 293ms/step - accuracy: 0.2218 - loss: 1.8423 - val_accuracy: 0.1400 - val_loss: 1.7773
- learning_rate: 1.0000e-04
Epoch 5/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 263ms/step - accuracy: 0.1979 - loss: 1.9078 - val_accuracy: 0.1400 - val_loss: 1.7416
- learning_rate: 1.0000e-04
Epoch 6/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 4s 277ms/step - accuracy: 0.1931 - loss: 1.8530 - val_accuracy: 0.1400 - val_loss: 1.7940
- learning_rate: 1.0000e-04
Epoch 7/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 4s 284ms/step - accuracy: 0.1796 - loss: 1.8090 - val_accuracy: 0.1400 - val_loss: 1.7807
- learning_rate: 1.0000e-04
Epoch 8/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 268ms/step - accuracy: 0.2410 - loss: 1.7824 - val_accuracy: 0.1400 - val_loss: 1.7852
- learning_rate: 1.0000e-04
Epoch 9/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 4s 284ms/step - accuracy: 0.1969 - loss: 1.8178 - val_accuracy: 0.1400 - val_loss: 1.7798
- learning_rate: 5.0000e-05
Epoch 10/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 269ms/step - accuracy: 0.1885 - loss: 1.8241 - val_accuracy: 0.1400 - val_loss: 1.7713
- learning_rate: 5.0000e-05
Epoch 11/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 270ms/step - accuracy: 0.2274 - loss: 1.7463 - val_accuracy: 0.1400 - val_loss: 1.7505
- learning_rate: 5.0000e-05
Epoch 12/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 269ms/step - accuracy: 0.1735 - loss: 1.7648 - val_accuracy: 0.1400 - val_loss: 1.7532
- learning_rate: 2.5000e-05
Epoch 13/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 275ms/step - accuracy: 0.1864 - loss: 1.7861 - val_accuracy: 0.1400 - val_loss: 1.7589
- learning_rate: 2.5000e-05
Epoch 14/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 267ms/step - accuracy: 0.2346 - loss: 1.7718 - val_accuracy: 0.1400 - val_loss: 1.7563
- learning_rate: 2.5000e-05
Epoch 15/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 253ms/step - accuracy: 0.2095 - loss: 1.7421 - val_accuracy: 0.1400 - val_loss: 1.7506
- learning_rate: 1.2500e-05
Epoch 16/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 260ms/step - accuracy: 0.2270 - loss: 1.7987 - val_accuracy: 0.1400 - val_loss: 1.7419
- learning_rate: 1.2500e-05
Epoch 17/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 268ms/step - accuracy: 0.2165 - loss: 1.7615 - val_accuracy: 0.1400 - val_loss: 1.7446
- learning_rate: 1.2500e-05
Epoch 18/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 4s 283ms/step - accuracy: 0.2267 - loss: 1.7777 - val_accuracy: 0.1400 - val_loss: 1.7454
- learning_rate: 6.2500e-06
Epoch 19/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 5s 264ms/step - accuracy: 0.2222 - loss: 1.7277 - val_accuracy: 0.1400 - val_loss: 1.7486
- learning_rate: 6.2500e-06
Epoch 20/20
13/13 ━━━━━━━━━━━━━━━━━━━━ 3s 267ms/step - accuracy: 0.2091 - loss: 1.7694 - val_accuracy: 0.1400 - val_loss: 1.7485
- learning_rate: 6.2500e-06
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step - accuracy: 0.1539 - loss: 1.7486
Test accuracy: 0.140
```

14 - Confusion Matrix Medium (5 random)

In [9]:

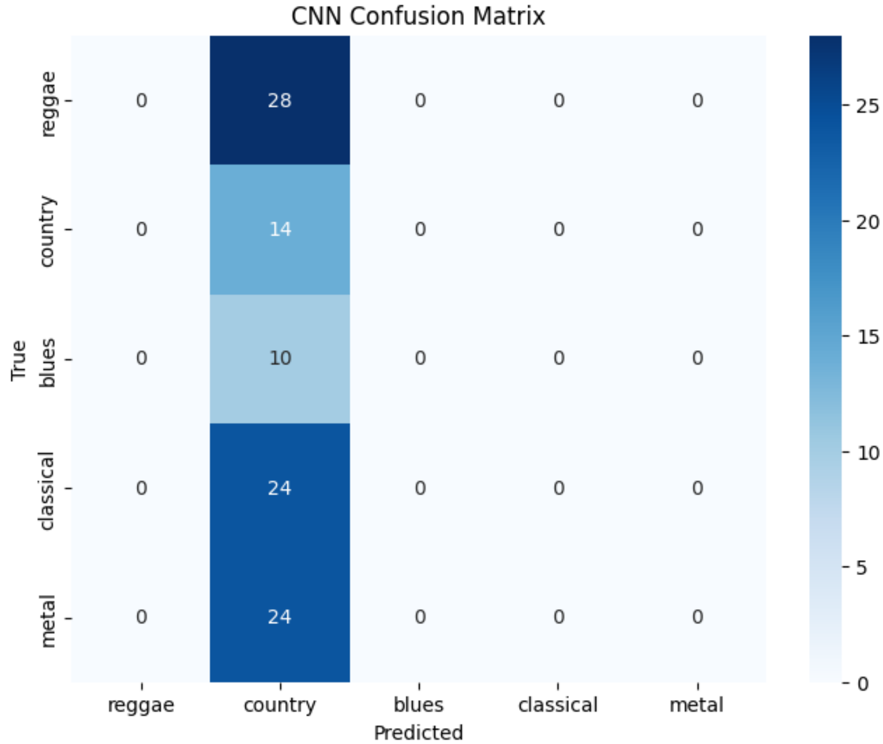
```python
import seaborn as sns
# from sklearn.metrics import confusion
import numpy as NP
from sklearn.metrics import confusion_matrix

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 56ms/step
```



In [ ]: