In [1]:
```
import pandas as tian
tian.set_option('display.max_columns', None)
import numpy as lumpnump
import matplotlib.pyplot as plt

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler, QuantileTrans
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix

import tensorflow as tf
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Input, Dense, Concatenate
from tensorflow.keras.activations import relu, sigmoid
from tensorflow.keras.losses import CategoricalCrossentropy, MeanSquaredErro
from tensorflow.keras.metrics import Precision, Recall
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.regularizers import l2
from tensorflow.keras.callbacks import TensorBoard
import seaborn as sns


import datetime
import gcsfs
from google.cloud import storage as gcs
from google.oauth2 import service_account as gsa

import os
from dotenv import load_dotenv
import certifi

os.environ['SSL_CERT_FILE'] = certifi.where()
top_tracks_stem = os.getenv('TOP_TRACKS_STEM')
```

In [2]:
```
load_dotenv()
# System variables
google_client_id = os.getenv('GOOGLE_CLIENT_ID')
google_client_secret = os.getenv('GOOGLE_CLIENT_SECRET')
google_project_id = os.getenv('GOOGLE_MUSIC_PROJECT')
google_bucket = os.getenv('GOOGLE_PRIMARY_BUCKET')
os.environ['GOOGLE_APPLICATION_CREDENTIALS'] = os.getenv('GOOGLE_SERVICE_CRE

# GCS setup details
bucket_file_base = f"gs://{google_bucket}/"
gcp_storage = gcs.Client()
gcp_primary_bucket = gcp_storage.bucket(google_bucket)
gcp_file_system = gcsfs.GCSFileSystem()
```

importing bigger files and creating subset I want for neural network

I only did this part once but kept it here so you can see what happened. It's commented out so I can hit "run all cells" without running these.

In [ ]:
```
# toptracks_bpmeta_matrix_csv = f"gs://{google_bucket}/silent_ascent_filesto
# toptracks_bpmeta_matrix_df = f"gs://{google_bucket}/silent_ascent_filestop
# toptracks_bpmeta_matrix_df_csv = '/Users/kevinkirby/Desktop/ml_local_csvs/
# toptracks_bpmeta_matrix_df = tian.read_csv(toptracks_bpmeta_matrix_df_csv)

# #matrix
# try:
#   fs = gcsfs.GCSFileSystem(project=google_project_id, token=os.getenv('GOO
#   with fs.open(toptracks_bpmeta_matrix_csv, 'rb') as f:
#     toptracks_bpmeta_matrix = lumpnump.genfromtxt(f, delimiter=',')
#     print('Download complete')
# except Exception as e:
#   print(f"Error: {e}")

# #df
# try:
#   fs = gcsfs.GCSFileSystem(project=google_project_id, token=os.getenv('GOO
#   with fs.open(toptracks_bpmeta_matrix_df, 'rb') as f:
#     toptracks_bpmeta_matrix_df = tian.read_csv(toptracks_bpmeta_matrix_df)
#     print('Download complete')
# except Exception as e:
#   print(f"Error: {e}")
```

In [ ]:
```
# toptracks_bpmeta_matrix_df.head()
```

In [ ]:
```
# toptracks_bpmeta_matrix_df_columns = toptracks_bpmeta_matrix_df.columns
# toptracks_bpmeta_matrix_df_dict = {name: idx for idx, name in enumerate(to
# toptracks_bpmeta_matrix_df_dict
```

eda + smaller file

eda

In [ ]:
```
# toptracks_bpmeta_matrix_df.nunique()
```

In [ ]:
```
# # creates some charts to help figure out where the data hangs out
# def metric_breakouts(dataframe, metric, percent_intervals):
#     interval = tian.cut(dataframe[metric], bins=percent_intervals)
#     metric_rows = dataframe.groupby(interval, observed=False).size()
#     intervals_df = metric_rows.reset_index()
#     intervals_df.columns = [f'{metric} range', 'row_count']
#     all_rows = intervals_df['row_count'].sum()
#     intervals_df['% of total'] = (intervals_df['row_count'] / all_rows) *
#     intervals_df = intervals_df.sort_values(by='row_count', ascending=Fals
#     return intervals_df

# def count_unique_in_intervals(dataframe, interval_field, count_field, inte
#     dataframe = dataframe.sort_values(by=interval_field, ascending=False)
#     num_intervals = 100 // interval
```

```
#     intervals = tian.cut(range(len(dataframe)), bins=num_intervals, labels
#     dataframe['interval'] = intervals
#     unique_rows = dataframe.groupby('interval')[count_field].nunique().res

#     return unique_rows
```

In [ ]:
```
# label_points = toptracks_bpmeta_matrix_df.groupby('label_id')['points'].su
# total_points = label_points.sum()
# top_20_labels = label_points.nlargest(20)
# top_20_labels_percentage = (top_20_labels / total_points) * 100
# top_labels_df = tian.DataFrame({
#     'points_sum': top_20_labels,
#     'percentage_of_total': top_20_labels_percentage
# })

# print(top_labels_df)
```

In [ ]:
```
# label_df = count_unique_in_intervals(toptracks_bpmeta_matrix_df, 'points',
# print(label_df)
```

In [ ]:
```
# bpm_interval = range(0, 310, 10)
# bpm_metrics_df = metric_breakouts(toptracks_bpmeta_matrix_df, 'bpm', bpm_i
# bpm_metrics_df = bpm_metrics_df.sort_values(by='bpm range', ascending=True
# print(bpm_metrics_df)
```

histogram and box plots by metric

In [ ]:
```
histo_box_plot(toptracks_bpmeta_matrix_df, metric_ids)
```

time series histogram by metric and year

In [ ]:
```
time_series_histo(toptracks_bpmeta_matrix_df, metric_ids, 'release_year')
```

smaller df/matrix based on eda

In [ ]:
```
# #columns to have in final new df
# selected_columns = ['isrc_numeric', 'release_year', 'label_percent_interva
#                     'duration', 'bpm_group', 'key_id', 'mode', 'valence',

# # clearing out years that I don't need
# filtered_df = toptracks_bpmeta_matrix_df.loc[
#     (toptracks_bpmeta_matrix_df['release_year'] >= 2019.0) &
#     (toptracks_bpmeta_matrix_df['release_year'] <= 2024.0)
# ].copy()

# # grouping labels in % intervals based on points
# filtered_df.loc[:, 'label_percent_interval'] = tian.qcut(filtered_df['poir

# #bpm range
# bpm_range = [0, 60, 100, 110, 120, 130, 140, 150, 300]
# filtered_df.loc[:, 'bpm_group'] = tian.cut(filtered_df['bpm'], bpm_range,

# # smashing bpm ranges together to create float
```

```
# filtered_df['bpm_group'] = filtered_df['bpm_group'].apply(lambda x: float(

# pogi_soar_matrix_df = filtered_df[selected_columns]
# pogi_soar_matrix = pogi_soar_matrix_df.to_numpy()
```

In [ ]:
```
# pogi_soar_matrix_df.head()
```

In [ ]:
```
# print(pogi_soar_matrix_df.isna().sum())
```

In [ ]:
```
# gcp export
# pogi_soar_matrix_df_csv = "pogi_soar_matrix_df.csv"
# pogi_soar_matrix_csv = "pogi_soar_matrix.csv"

# pogi_soar_matrix_df.to_csv(pogi_soar_matrix_df_csv, index=False)
# lumpnump.savetxt(pogi_soar_matrix_csv, pogi_soar_matrix, delimiter=',')

# # Upload to Google Cloud Storage
# def upload_to_gcs(source_file_name, destination_blob_name):
#     blob = gcp_primary_bucket.blob(destination_blob_name)
#     blob.upload_from_filename(source_file_name)

# upload_to_gcs(pogi_soar_matrix_df_csv, f"top_tracks_tables/{pogi_soar_matr
# upload_to_gcs(pogi_soar_matrix_csv, f"top_tracks_tables/{pogi_soar_matrix_

# print("upload complete")
```

Import of new and smaller matrix from GCP

This is so I don't have to run all of the above every time. I've saved it to show my work.

In [3]:
```
pogi_soar_matrix_csv = f"gs://{google_bucket}/silent_ascent_files/pogi_soar_

try:
  fs = gcsfs.GCSFileSystem(project=google_project_id, token=os.getenv('GOOGL
  with fs.open(pogi_soar_matrix_csv, 'rb') as f:
    pogi_soar_matrix = lumpnump.genfromtxt(f, delimiter=',')
    print('Download complete')
except Exception as e:
  print(f"Error: {e}")
```

```
Download complete
```

In [4]:
```
#this is a dictionary of indexes from the matrix and a corresponding df not
pogi_soar_dict = {
    0: {'name': 'isrc_numeric',
        'sample_value_df': 7218192100041,
        'sample_value_matrix': 7218192100041,
        'unique_count': 75701},
    1: {'name': 'release_year',
        'sample_value_df': 2021,
        'sample_value_matrix': 2021,
        'unique_count': 5},
    2: {'name': 'label_percent_interval',
```

```
        'sample_value_df': 0.95,
        'sample_value_matrix': 0.95,
        'unique_count': 20},
    3: {'name': 'genre_id_x',
        'sample_value_df': 12,
        'sample_value_matrix': 12,
        'unique_count': 32},
    4: {'name': 'duration',
        'sample_value_df': 445,
        'sample_value_matrix': 445,
        'unique_count': 693},
    5: {'name': 'bpm_group',
        'sample_value_df': 120130.0,
        'sample_value_matrix': 120120.0,
        'unique_count': 8},
    6: {'name': 'key_id',
        'sample_value_df': 4,
        'sample_value_matrix': 4,
        'unique_count': 34},
    7: {'name': 'mode',
        'sample_value_df': 0,
        'sample_value_matrix': 0,
        'unique_count': 2},
    8: {'name': 'valence',
        'sample_value_df': 0.473,
        'sample_value_matrix': 0.473,
        'unique_count': 1678},
    9: {'name': 'points',
        'sample_value_df': 35920,
        'sample_value_matrix': 35920,
        'unique_count': 7286}
}
```

neural work

In [5]:

```
two_layer_inputs = [1, 2, 6, 7]
inputs = pogi_soar_matrix[:, two_layer_inputs]

# genre ID, bpm_group, valence as targets
two_layer_targets = [3, 5, 8]
targets = pogi_soar_matrix[:, two_layer_targets]

# Get unique categories (sanity check)
year_uniques = set(inputs[:, 0])
label_percent_uniques = set(inputs[:, 1])
key_uniques = set(inputs[:, 2])
mode_uniques = set(inputs[:, 3])

print(f'input years: {year_uniques}')
print(f'input label %: {label_percent_uniques}')
print(f'input keys: {key_uniques}')
print(f'input modes: {mode_uniques}')

genre_uniques = set(targets[:, 0])
bpm_uniques = set(targets[:, 1])
```

```
valence_uniques = list(set(targets[:, 2]))

print(f'target genres: {genre_uniques}')
print(f'target bpms: {bpm_uniques}')
print(f'target valence (example): {valence_uniques[:10]}')
```

```
input years: {2019.0, 2020.0, 2021.0, 2022.0, 2023.0}
input label %: {0.95, 0.9, 0.85, 0.8, 0.75, 0.7, 0.65, 0.6, 0.55, 0.5, 0.25,
0.0, 0.35, 0.05, 0.45, 0.2, 0.15, 0.1, 0.3, 0.4}
input keys: {1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0, 10.0, 11.0, 12.0,
13.0, 14.0, 15.0, 16.0, 17.0, 18.0, 19.0, 20.0, 21.0, 22.0, 23.0, 24.0, 25.
0, 26.0, 27.0, 28.0, 29.0, 30.0, 31.0, 32.0, 33.0, 34.0}
input modes: {0.0, 1.0}
target genres: {1.0, 2.0, 3.0, 5.0, 6.0, 7.0, 8.0, 9.0, 11.0, 12.0, 13.0, 1
4.0, 15.0, 18.0, 37.0, 38.0, 39.0, 50.0, 81.0, 85.0, 86.0, 89.0, 90.0, 91.0,
92.0, 93.0, 94.0, 95.0, 96.0, 97.0, 98.0, 99.0}
target bpms: {120130.0, 60100.0, 110120.0, 100110.0, 130140.0, 60.0, 140150.
0, 150300.0}
target valence (example): [0.375, 0.593, 0.5, 0.125, 0.25, 0.875, 0.75, 0.62
5, 0.718, 0.968]
```

In [7]:

```
def quantile_transform_data(data):
    transformer = QuantileTransformer(output_distribution='normal')
    return transformer.fit_transform(data.reshape(-1, 1)).flatten()

# valence quantile transform
valence_index = two_layer_targets.index(8)
valence_data = targets[:, valence_index]
valence_transformed = quantile_transform_data(valence_data)
targets[:, valence_index] = valence_transformed

# transformers for categorical and numerical data
categorical_transformer = OneHotEncoder(sparse_output=False)
numerical_transformer = MinMaxScaler()

input_preprocessor = ColumnTransformer(
    transformers=[
        ('categorical', categorical_transformer, [0, 1, 2, 3])
    ]
)

target_preprocessor = ColumnTransformer(
    transformers=[
        ('categorical', categorical_transformer, [0, 1]),
        ('numerical', numerical_transformer, [2])
    ]
)

# check original shape
print("Original matrix shape:", pogi_soar_matrix.shape)

# transform inputs and outputs
inputs_transformed = input_preprocessor.fit_transform(inputs)
print("Transformed inputs shape:", inputs_transformed.shape)

targets_transformed = target_preprocessor.fit_transform(targets)
```

```
print("Transformed targets shape:", targets_transformed.shape)

# train/validate/test split
X_train, X_temp, y_train, y_temp = train_test_split(inputs_transformed, targ
X_cv, X_test, y_cv, y_test = train_test_split(X_temp, y_temp, test_size=0.50

# post-split check
print("X_train.shape:", X_train.shape)
print("y_train.shape:", y_train.shape)
print("X_cv.shape:", X_cv.shape)
print("y_cv.shape:", y_cv.shape)
print("X_test.shape:", X_test.shape)
print("y_test.shape:", y_test.shape)

# train, validate, and test input sets based on where each feature lies as c
X_train_year = X_train[:, :4]
X_train_label = X_train[:, 4:24]
X_train_key = X_train[:, 24:58]
X_train_mode = X_train[:, 58:]

print("X_train_year:", X_train_year.shape)
print("X_train_label:", X_train_label.shape)
print("X_train_key:", X_train_key.shape)
print("X_train_mode:", X_train_mode.shape)

X_cv_year = X_cv[:, :4]
X_cv_label = X_cv[:, 4:24]
X_cv_key = X_cv[:, 24:58]
X_cv_mode = X_cv[:, 58:]

print("X_cv_year:", X_cv_year.shape)
print("X_cv_label:", X_cv_label.shape)
print("X_cv_key:", X_cv_key.shape)
print("X_cv_mode:", X_cv_mode.shape)

X_test_year = X_test[:, :4]
X_test_label = X_test[:, 4:24]
X_test_key = X_test[:, 24:58]
X_test_mode = X_test[:, 58:]
print("X_test_year:", X_test_year.shape)
print("X_test_label:", X_test_label.shape)
print("X_test_key:", X_test_key.shape)
print("X_test_mode:", X_test_mode.shape)

# train, validate, and test output sets based on where each feature lies as
y_train_genre = y_train[:, :len(genre_uniques)]
y_train_bpm = y_train[:, len(genre_uniques):(len(genre_uniques) + len(bpm_ur
y_train_valence = y_train[:, -1]  # Last column for valence

print("y_train_genre:", y_train_genre.shape)
print("y_train_bpm:", y_train_bpm.shape)
print("y_train_valence:", y_train_valence.shape)

y_cv_genre = y_cv[:, :len(genre_uniques)]
y_cv_bpm = y_cv[:, len(genre_uniques):(len(genre_uniques) + len(bpm_uniques)
y_cv_valence = y_cv[:, -1]
```

```
y_test_genre = y_test[:, :len(genre_uniques)]
y_test_bpm = y_test[:, len(genre_uniques):(len(genre_uniques) + len(bpm_unic
y_test_valence = y_test[:, -1]

print("y_cv_genre:", y_cv_genre.shape)
print("y_cv_bpm:", y_cv_bpm.shape)
print("y_cv_valence:", y_cv_valence.shape)

print("y_test_genre:", y_test_genre.shape)
print("y_test_bpm:", y_test_bpm.shape)
print("y_test_valence:", y_test_valence.shape)
```

```
Original matrix shape: (89932, 10)
Transformed inputs shape: (89932, 61)
Transformed targets shape: (89932, 41)
X_train.shape: (53959, 61)
y_train.shape: (53959, 41)
X_cv.shape: (17986, 61)
y_cv.shape: (17986, 41)
X_test.shape: (17987, 61)
y_test.shape: (17987, 41)
X_train_year: (53959, 4)
X_train_label: (53959, 20)
X_train_key: (53959, 34)
X_train_mode: (53959, 3)
X_cv_year: (17986, 4)
X_cv_label: (17986, 20)
X_cv_key: (17986, 34)
X_cv_mode: (17986, 3)
X_test_year: (17987, 4)
X_test_label: (17987, 20)
X_test_key: (17987, 34)
X_test_mode: (17987, 3)
y_train_genre: (53959, 32)
y_train_bpm: (53959, 8)
y_train_valence: (53959,)
y_cv_genre: (17986, 32)
y_cv_bpm: (17986, 8)
y_cv_valence: (17986,)
y_test_genre: (17987, 32)
y_test_bpm: (17987, 8)
y_test_valence: (17987,)
```

In [11]:
```
def pogi_prep(input_shape):
    soigneur = Sequential([
        Input(shape=(input_shape,)),
        Dense(25, activation='relu', kernel_regularizer=l2(0.01)),
        Dense(17, activation='relu', kernel_regularizer=l2(0.01)),
    ])
    return soigneur
```

In [12]:
```
def pogi_slay():
    label_input = Input(shape=(20,), name='label_percent_interval')
    key_input = Input(shape=(34,), name='key')
    mode_input = Input(shape=(3,), name='mode')
```

```
    release_year_input = Input(shape=(4,), name='release_year')  # One-hot e

    # uae pogi_prep to create subnetwork for each input
    label_features = pogi_prep(20)(label_input)
    key_features = pogi_prep(34)(key_input)
    mode_features = pogi_prep(3)(mode_input)
    release_year_features = pogi_prep(4)(release_year_input)

    # string together the different features for use in combined model
    false_flat = Concatenate()([label_features, key_features, mode_features,

    # combined model hidden layers
    dolly_hidden = Dense(13, activation='relu', kernel_regularizer=l2(0.1))(
    pogi_hidden = Dense(10, activation='relu', kernel_regularizer=l2(0.1))(d

    # final outputs

    #32 genres
    genre_slay = Dense(32, activation='softmax', name='genre_id')(pogi_hidde

    # 8 BPM groups created
    bpm_4tofloor = Dense(8, activation='softmax', name='bpm_group')(pogi_hid

    #single output ranging from 0 to 1 on continuous scale
    valence_smile = Dense(1, activation='sigmoid', name='valence')(pogi_hidd

    # defines final model
    pogi_wheels = Model(inputs=[label_input, key_input, mode_input, release_
                        outputs=[genre_slay, bpm_4tofloor, valence_smile])

    return pogi_wheels
```

In [13]:

```
#executes and compiles final model
ventoux_summit = pogi_slay()

ventoux_summit.compile(
    #adamds optimizer alllows for automatic adjustments of learning rate in
    optimizer=Adam(learning_rate=0.001),
    loss={
        'genre_id': CategoricalCrossentropy(),
        'bpm_group': CategoricalCrossentropy(),
        'valence': MeanSquaredError()
    },
    metrics={
        'genre_id': ['accuracy', Precision(), Recall()],
        'bpm_group': ['accuracy', Precision(), Recall()],
        'valence': 'mean_squared_error'
    }
)
```

```
2024-08-15 00:46:07.209961: I metal_plugin/src/device/metal_device.cc:1154]
Metal device set to: Apple M3 Max
2024-08-15 00:46:07.210015: I metal_plugin/src/device/metal_device.cc:296] s
ystemMemory: 128.00 GB
2024-08-15 00:46:07.210026: I metal_plugin/src/device/metal_device.cc:313] m
axCacheSize: 48.00 GB
2024-08-15 00:46:07.210063: I tensorflow/core/common_runtime/pluggable_devic
e/pluggable_device_factory.cc:305] Could not identify NUMA node of platform
GPU ID 0, defaulting to 0. Your kernel may not have been built with NUMA sup
port.
2024-08-15 00:46:07.210086: I tensorflow/core/common_runtime/pluggable_devic
e/pluggable_device_factory.cc:271] Created TensorFlow device (/job:localhos
t/replica:0/task:0/device:GPU:0 with 0 MB memory) -> physical PluggableDevic
e (device: 0, name: METAL, pci bus id: <undefined>)
```

model run

In [14]:

```
pogi_stem = f'{bucket_file_base}/silent_ascent_files/pogi_logs'
pogi_logger = f'{pogi_stem}/{datetime.datetime.now().strftime("%Y%m%d-%H%M%S

pogi_monitoring = TensorBoard(log_dir=pogi_logger, histogram_freq=1)

#fitting
pogi_soar = ventoux_summit.fit(
    [X_train_label, X_train_key, X_train_mode, X_train_year],
    {'genre_id': y_train_genre, 'bpm_group': y_train_bpm, 'valence': y_trair
    epochs=10,
    batch_size=100,
     validation_data=(
     [X_cv_label, X_cv_key, X_cv_mode, X_cv_year],
     {'genre_id': y_cv_genre, 'bpm_group': y_cv_bpm, 'valence': y_cv_valence
        ),
    callbacks=[pogi_monitoring]
    )
```

```
Epoch 1/10
```

```
2024-08-15 00:46:16.673604: I tensorflow/core/grappler/optimizers/custom_gra
ph_optimizer_registry.cc:117] Plugin optimizer for device_type GPU is enable
d.
```

```
540/540 ━━━━━━━━━━━━━━━━━━━━ 44s 78ms/step - bpm_group_accuracy: 0.4058 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
accuracy: 0.0462 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 7.3870 - valence_mean_squared_error: 0.0105 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0537 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 5.0403 - val_valence_me
an_squared_error: 0.0095
Epoch 2/10
540/540 ━━━━━━━━━━━━━━━━━━━━ 40s 74ms/step - bpm_group_accuracy: 0.4235 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
accuracy: 0.0509 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 4.9933 - valence_mean_squared_error: 0.0096 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0533 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 4.9708 - val_valence_me
an_squared_error: 0.0095
Epoch 3/10
540/540 ━━━━━━━━━━━━━━━━━━━━ 41s 77ms/step - bpm_group_accuracy: 0.4192 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
accuracy: 0.0528 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 4.9626 - valence_mean_squared_error: 0.0093 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0563 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 4.9673 - val_valence_me
an_squared_error: 0.0095
Epoch 4/10
540/540 ━━━━━━━━━━━━━━━━━━━━ 40s 74ms/step - bpm_group_accuracy: 0.4220 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
accuracy: 0.0510 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 4.9606 - valence_mean_squared_error: 0.0093 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0537 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 4.9675 - val_valence_me
an_squared_error: 0.0095
Epoch 5/10
540/540 ━━━━━━━━━━━━━━━━━━━━ 40s 74ms/step - bpm_group_accuracy: 0.4211 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
accuracy: 0.0513 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 4.9609 - valence_mean_squared_error: 0.0094 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0537 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 4.9668 - val_valence_me
an_squared_error: 0.0095
Epoch 6/10
540/540 ━━━━━━━━━━━━━━━━━━━━ 41s 76ms/step - bpm_group_accuracy: 0.4222 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
accuracy: 0.0523 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 4.9648 - valence_mean_squared_error: 0.0094 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0537 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 4.9664 - val_valence_me
an_squared_error: 0.0095
Epoch 7/10
540/540 ━━━━━━━━━━━━━━━━━━━━ 41s 76ms/step - bpm_group_accuracy: 0.4230 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
```

```
accuracy: 0.0509 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 4.9548 - valence_mean_squared_error: 0.0096 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0537 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 4.9665 - val_valence_me
an_squared_error: 0.0095
Epoch 8/10
540/540 ━━━━━━━━━━━━━━━━━━━━ 41s 76ms/step - bpm_group_accuracy: 0.4245 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
accuracy: 0.0506 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 4.9584 - valence_mean_squared_error: 0.0094 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0537 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 4.9672 - val_valence_me
an_squared_error: 0.0095
Epoch 9/10
540/540 ━━━━━━━━━━━━━━━━━━━━ 43s 80ms/step - bpm_group_accuracy: 0.4225 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
accuracy: 0.0532 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 4.9537 - valence_mean_squared_error: 0.0094 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0530 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 4.9664 - val_valence_me
an_squared_error: 0.0095
Epoch 10/10
540/540 ━━━━━━━━━━━━━━━━━━━━ 43s 80ms/step - bpm_group_accuracy: 0.4203 - bp
m_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_
accuracy: 0.0532 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e
+00 - loss: 4.9615 - valence_mean_squared_error: 0.0094 - val_bpm_group_accu
racy: 0.4175 - val_bpm_group_precision_1: 0.0000e+00 - val_bpm_group_recall_
1: 0.0000e+00 - val_genre_id_accuracy: 0.0537 - val_genre_id_precision: 0.00
00e+00 - val_genre_id_recall: 0.0000e+00 - val_loss: 4.9674 - val_valence_me
an_squared_error: 0.0095
```

plot predict

In [15]:

```
predictions = ventoux_summit.predict([X_test_label, X_test_key, X_test_mode,
```

```
563/563 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```

In [16]:

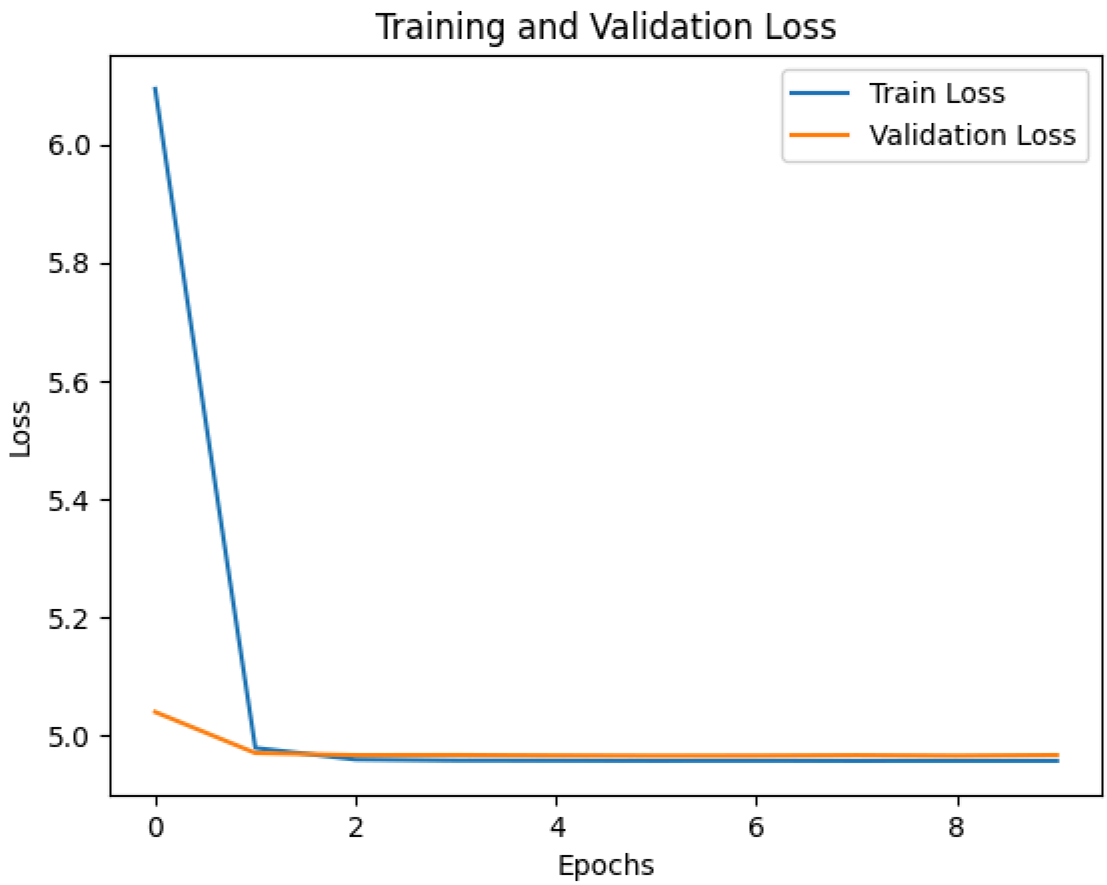
```
ventoux_evaluation = ventoux_summit.evaluate(
    [X_test_label, X_test_key, X_test_mode, X_test_year],
    {'genre_id': y_test_genre, 'bpm_group': y_test_bpm, 'valence': y_test_va
)
```

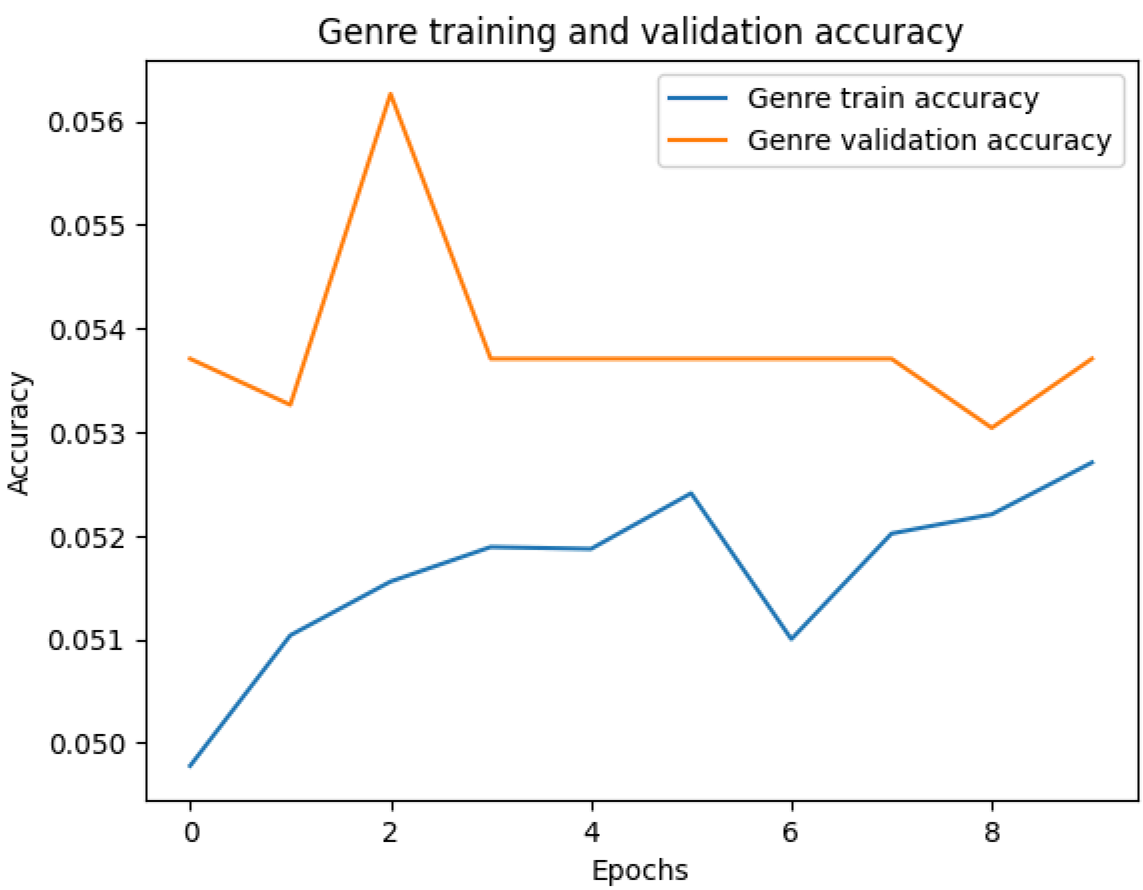
```
563/563 ━━━━━━━━━━━━━━━━━━━━ 7s 13ms/step - bpm_group_accuracy: 0.4164 - bpm
_group_precision_1: 0.0000e+00 - bpm_group_recall_1: 0.0000e+00 - genre_id_a
ccuracy: 0.0546 - genre_id_precision: 0.0000e+00 - genre_id_recall: 0.0000e+
00 - loss: 4.9721 - valence_mean_squared_error: 0.0096
```

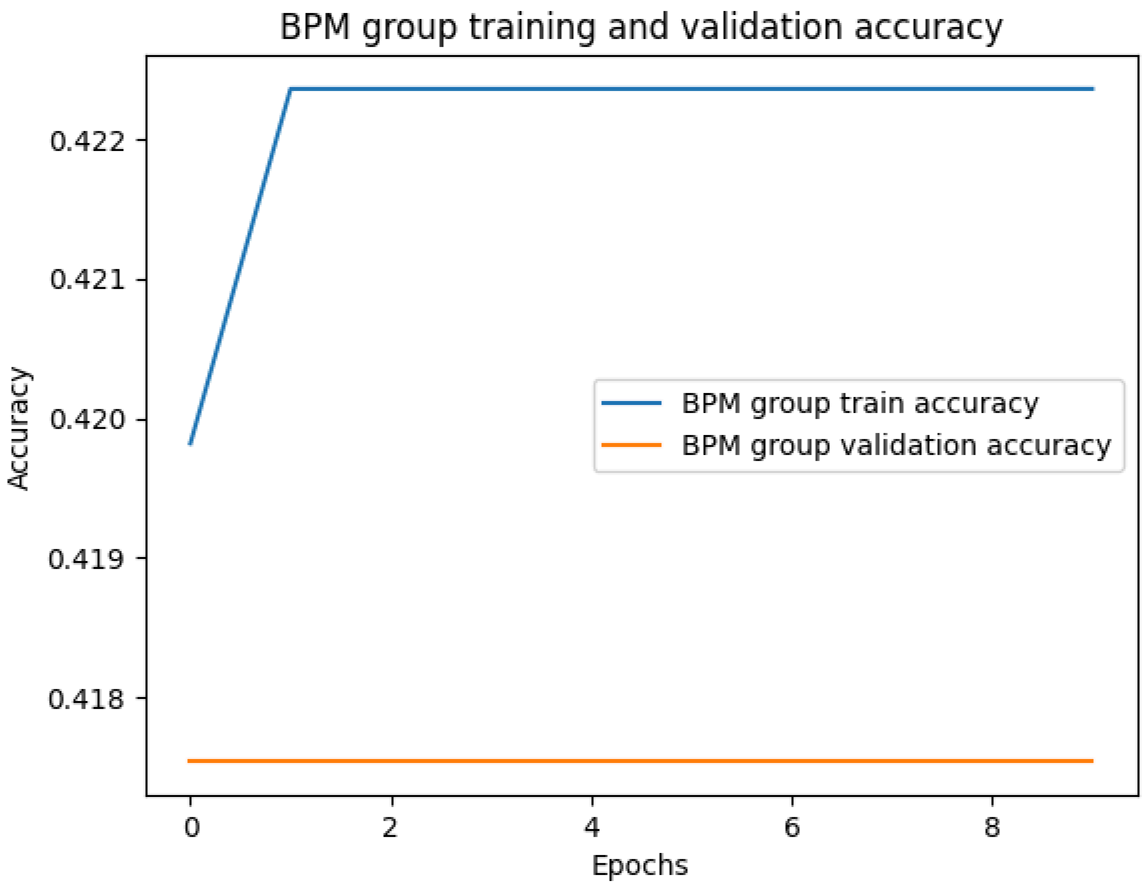
In [17]:

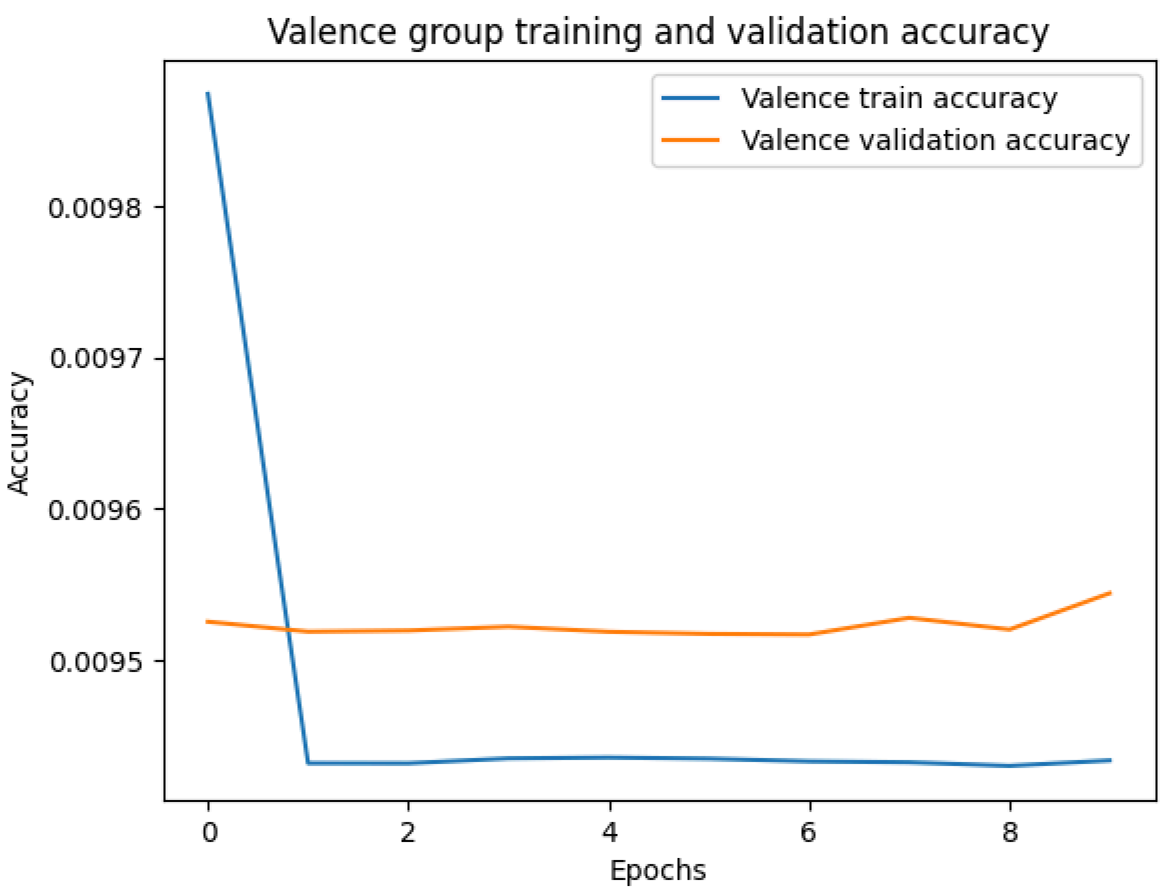
```
history = pogi_soar.history

# Plot training & validation loss values
plt.plot(history['loss'], label='Train Loss')
plt.plot(history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
```

```
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.show()

# You can also plot the metrics for each output (genre_id, bpm_group, valenc
plt.plot(history['genre_id_accuracy'], label='Genre train accuracy')
plt.plot(history['val_genre_id_accuracy'], label='Genre validation accuracy'
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Genre training and validation accuracy')
plt.legend()
plt.show()

plt.plot(history['bpm_group_accuracy'], label='BPM group train accuracy')
plt.plot(history['val_bpm_group_accuracy'], label='BPM group validation accu
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('BPM group training and validation accuracy')
plt.legend()
plt.show()

plt.plot(history['valence_mean_squared_error'], label='Valence train accurac
plt.plot(history['val_valence_mean_squared_error'], label='Valence validatic
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Valence group training and validation accuracy')
plt.legend()
plt.show()
```


Training and Validation Loss
Train Loss
Validation Loss
Loss
6.0
5.8
5.6
5.4
5.2
5.0
0
2
4
6
8
Epochs

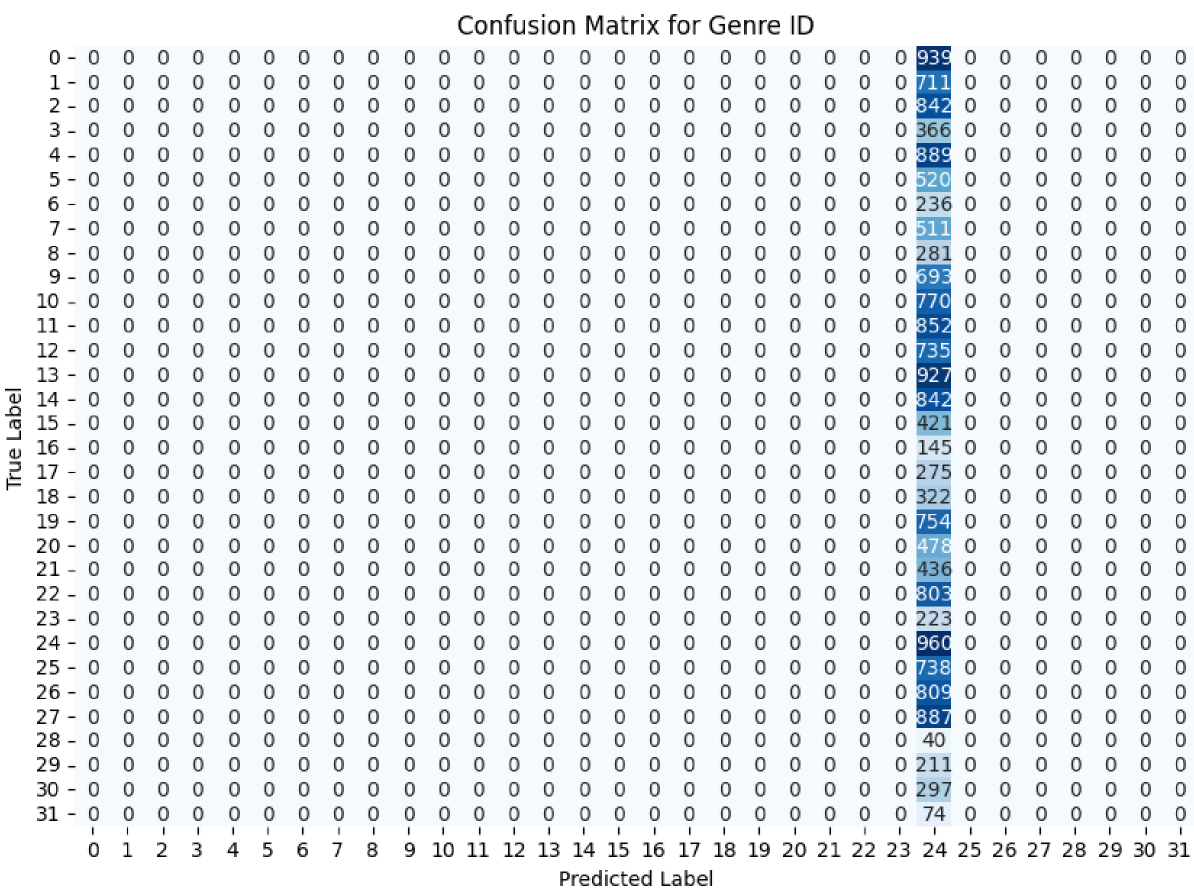

Genre training and validation accuracy
Genre train accuracy
Genre validation accuracy
Accuracy
0.056
0.055
0.054
0.053
0.052
0.051
0.050
0
2
4
6
8
Epochs

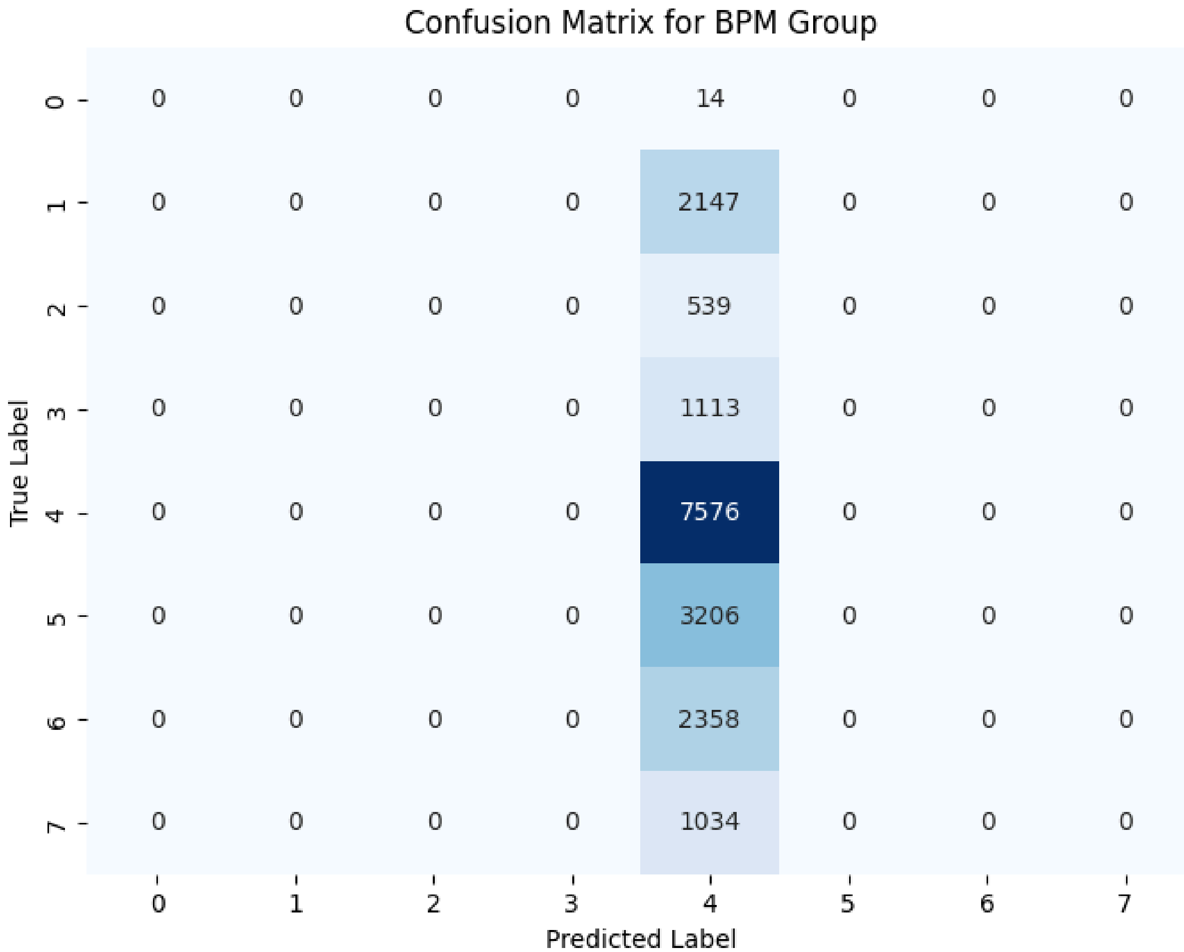

BPM group training and validation accuracy
0.422
0.421
0.420
0.419
0.418
Accuracy
BPM group train accuracy
BPM group validation accuracy
0
2
4
6
8
Epochs


Valence group training and validation accuracy
0.0098
0.0097
0.0096
0.0095
Accuracy
Valence train accuracy
Valence validation accuracy
0
2
4
6
8
Epochs

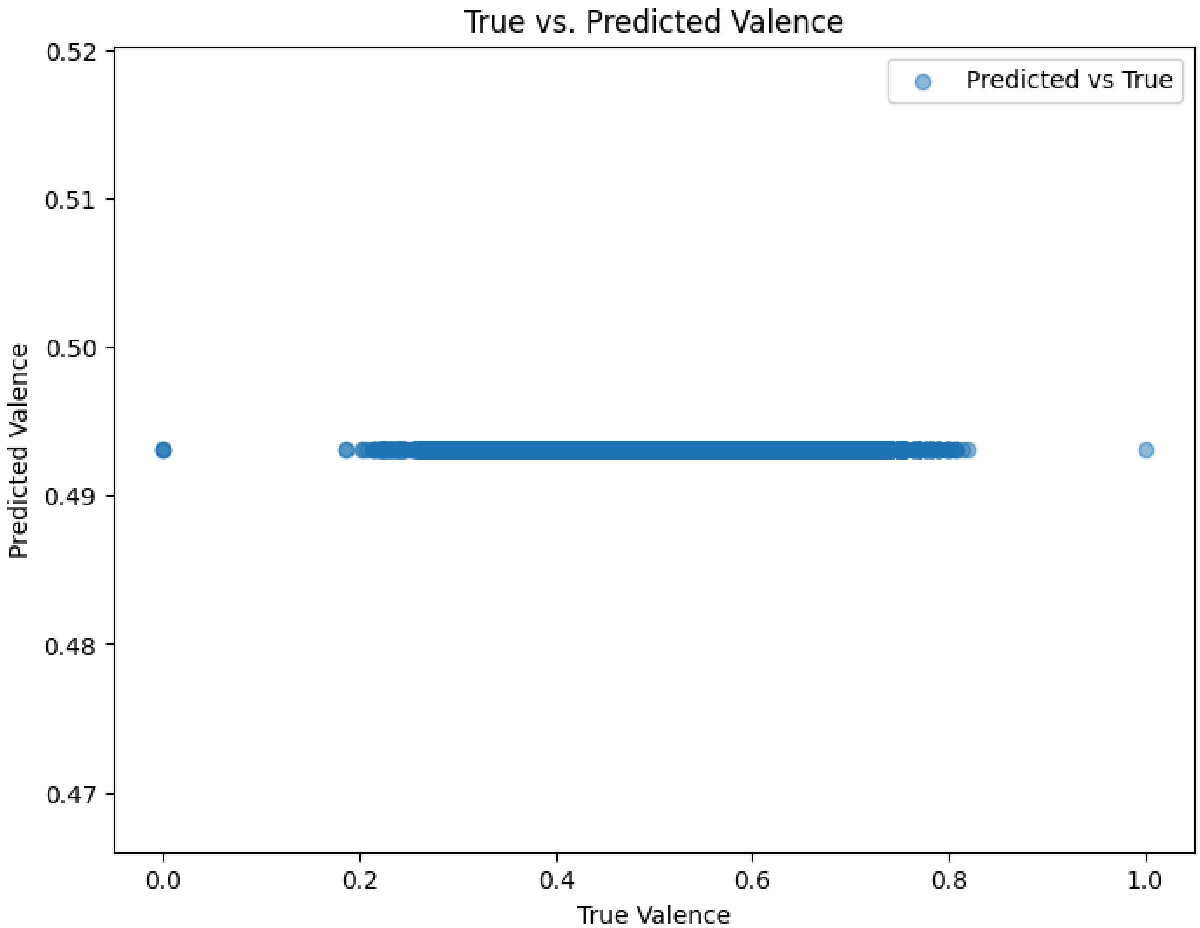
In [18]:

```python
#predited and actual genre and bpm group values
y_pred_genre = lumpnump.argmax(predictions[0], axis=1)
y_true_genre = lumpnump.argmax(y_test_genre, axis=1)

y_pred_bpm = lumpnump.argmax(predictions[1], axis=1)
y_true_bpm = lumpnump.argmax(y_test_bpm, axis=1)

# confusion matrices for genre and bpm group
cm_genre = confusion_matrix(y_true_genre, y_pred_genre)
plt.figure(figsize=(10, 7))
sns.heatmap(cm_genre, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix for Genre ID')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()

# Plot confusion matrix for bpm_group
cm_bpm = confusion_matrix(y_true_bpm, y_pred_bpm)
plt.figure(figsize=(8, 6))
sns.heatmap(cm_bpm, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.title('Confusion Matrix for BPM Group')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```





In [19]:
```
#prediction and actual values for valence
y_pred_valence = predictions[2].flatten()
y_true_valence = y_test_valence

plt.figure(figsize=(8, 6))
plt.scatter(y_true_valence, y_pred_valence, alpha=0.5, label='Predicted vs T
plt.xlabel('True Valence')
plt.ylabel('Predicted Valence')
plt.title('True vs. Predicted Valence')
plt.legend()
plt.show()
```


True vs. Predicted Valence
Predicted vs True
Predicted Valence
True Valence
0.52
0.51
0.50
0.49
0.48
0.47
0.0
0.2
0.4
0.6
0.8
1.0

```
In [ ]:
```