Schritt 2 Deep Learning: Instrumenten-Klassifikation

Import libraries

In [1]:
```
import os
import numpy as np
import librosa as lr
import pandas as pd
import keras
import pickle
import keras.initializers
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns

from tqdm import tqdm
from keras.layers import Conv2D, MaxPool2D, Flatten, Dense, Dropout
from keras.models import Sequential
from keras.regularizers import l2
from sklearn.model_selection import train_test_split
from sklearn.metrics import recall_score, precision_score, accuracy_score
from sklearn.metrics import confusion_matrix, f1_score, classification_report
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

In [2]:
```
print("Num GPUs Available: ", len(tf.config.experimental.list_physical_devices('GPU')))
```
```
Num GPUs Available:  1
```

In [3]:
```
# Set directory for source files

ROOT = "all_samples_wav"
folders = os.listdir(ROOT) # names of subfolders
file_data = [] # filenames in each of the 58 folders

TARGET_SECONDS = 2
sr = 22050
target_num_samples = sr*TARGET_SECONDS

n_fft = 1024
hop_length = 512
n_mfcc = 13
```

Statistics about the dataset

In [4]:
```
for label in tqdm(range(len(folders))):
    sub_dir = os.listdir(f'{ROOT}/{folders[label]}')
    file_data.append(sub_dir)
```
```
100%|████████████████████████████████████████| 20/20 [00:00<00:00, 25.18it/s]
```

In [5]:
```
amounts = []

for i in range(len(file_data)):
    amounts.append(len(file_data[i]))
col1 = np.array(folders)
col2 = np.array(amounts)
merge = {'folder': col1, 'amount': col2}

df = pd.DataFrame(merge, columns=['folder', 'amount'])

print(f'Total amount of samples: {sum(amounts)}')

df
```
```
Total amount of samples: 13681
```

Out[5]:

	folder	amount
0	banjo	74
1	bassoon	720
2	bass_clarinet	944
3	cello	889
4	clarinet	846
5	contrabassoon	710
6	cor_anglais	691
7	double_bass	852
8	flute	878
9	french_horn	652
10	guitar	106
11	mandolin	80
12	oboe	596
13	percussion	148
14	saxophone	732
15	trombone	831
16	trumpet	485
17	tuba	972
18	viola	973
19	violin	1502

Load audio data

In [6]:
```
# audio_data = []
#
# for dirname, _, filenames in tqdm(os.walk(ROOT)):
#     for filename in filenames:
#         src = f'{dirname}/{filename}'
#         audio_data.append(lr.load(src))
```

Save/Load audio_waves array

In [7]:
```
# Save
# with open('audio_data.pickle', 'wb') as f:
#     pickle.dump(audio_data, f)
```

In [8]:
```
# Load
with open('audio_data.pickle', 'rb') as f:
    audio_data = pickle.load(f)
```

Create dataframe overview

In [9]:
```
fname = []
classID = []
num_samples = []

df1 = pd.DataFrame(np.array(audio_data, dtype=object), columns=['signal', 'samplerate'])

for i in range(df1.shape[0]):
    num_samples.append(len(df1['signal'].iloc[i]))
num_samples = np.array(num_samples)

for dirname, _, filenames in os.walk(ROOT):
    for filename in filenames:
        fname.append(filename)
        classID.append(dirname[16:])
fname = np.array(fname)
classID = np.array(classID)

df1['num samples'] = num_samples
df1['seconds'] = df1['num samples']/df1['samplerate']
df1['fname'] = fname
df1['classID'] = classID

# round seconds
df1['seconds'] = df1['seconds'].apply(pd.to_numeric, errors='coerce').round(1)

df1
```

Out[9]:

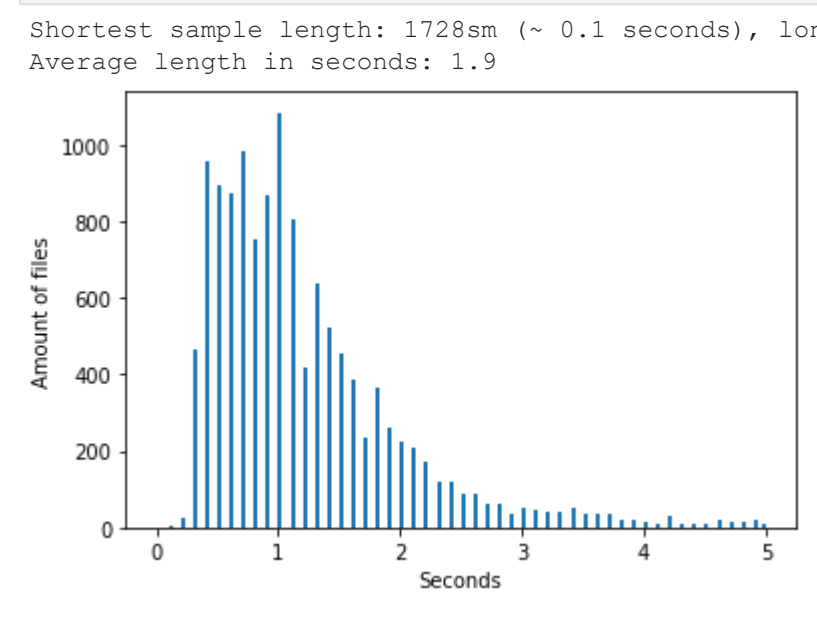
	signal	samplerate	num samples	seconds	fname	classID
0	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	76608	3.5	banjo_A3_very-long_forte_normal.wav	banjo
1	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	77184	3.5	banjo_A3_very-long_piano_normal.wav	banjo
2	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	84096	3.8	banjo_A4_very-long_forte_normal.wav	banjo
3	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	69696	3.2	banjo_A4_very-long_piano_normal.wav	banjo
4	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	85248	3.9	banjo_A5_very-long_forte_normal.wav	banjo
...	...	...	...	...	...	...
13676	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	48960	2.2	violin_Gs6_1_mezzo-forte_natural-harmonic.wav	violin
13677	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	28800	1.3	violin_Gs6_1_piano_arco-sul-tasto.wav	violin
13678	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	34560	1.6	violin_Gs6_1_piano_natural-harmonic.wav	violin
13679	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	51840	2.4	violin_Gs6_phrase_pianissimo_arco-normal.wav	violin
13680	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22050	31680	1.4	violin_Gs7_1_mezzo-forte_natural-harmonic.wav	violin

13681 rows × 6 columns

In [10]:
```
%matplotlib inline
x = df1['seconds']

plt.hist(x, density=False, bins=150, range=(0,5))  # density=False would make counts
plt.ylabel('Amount of files')
plt.xlabel('Seconds');

print(f"Shortest sample length: {np.min(df1['num samples'])}sm (~ {np.min(df1['seconds'])} seconds), longest: {
print(f"Average length in seconds: {np.round(np.mean(df1['seconds']), decimals=1)}")
```
```
Shortest sample length: 1728sm (~ 0.1 seconds), longest: 1711296sm (~ 77.6 seconds)
Average length in seconds: 1.9
```



Bring all soundfiles to the desired length of 2 seconds

In [11]:
```
processed_audio = []

for i in range(len(audio_data)):
    signal = audio_data[i][0]

    # shorten if too long, right-pad if too short
    if len(signal) > target_num_samples:
        processed_audio.append(signal[:target_num_samples])

    if len(signal) < target_num_samples:
        num_missing_samples = target_num_samples - len(signal)
        last_dim_padding = (0, num_missing_samples)
        processed_audio.append(np.pad(signal, last_dim_padding, mode='constant'))

processed_audio = np.array(processed_audio, dtype=float)
```

Save/load processed_audio_data

In [12]:
```
# Save
# with open('processed_audio.pickle', 'wb') as f:
#     pickle.dump(processed_audio, f)
```

In [13]:
```
# Load
with open('processed_audio.pickle', 'rb') as f:
    processed_audio = pickle.load(f)
```

In [14]:
```
processed_audio.shape
```
Out[14]:
```
(13681, 44100)
```

Feature extraction

Methods and extraction

In [15]:
```
def mfcc_scale(mfcc):
    scaler = StandardScaler()
    mfcc = scaler.fit_transform(np.array(mfcc))
    return mfcc

def calc_mfcc(signal):
    return lr.feature.mfcc(y=signal, n_mfcc=n_mfcc, sr=sr)
```

In [16]:
```
mfcc_features = []

for i in tqdm(range(len(processed_audio))):
    mfcc_features.append(mfcc_scale(calc_mfcc(processed_audio[i])))

mfcc_features = np.array(mfcc_features)
```
```
100%|████████████████████████████████████████| 13681/13681 [01:48<00:00, 126.56it/s]
```

Save/load mfcc_features

In [17]:
```
# Save
with open('mfcc_features.pickle', 'wb') as f:
    pickle.dump(mfcc_features, f)
```

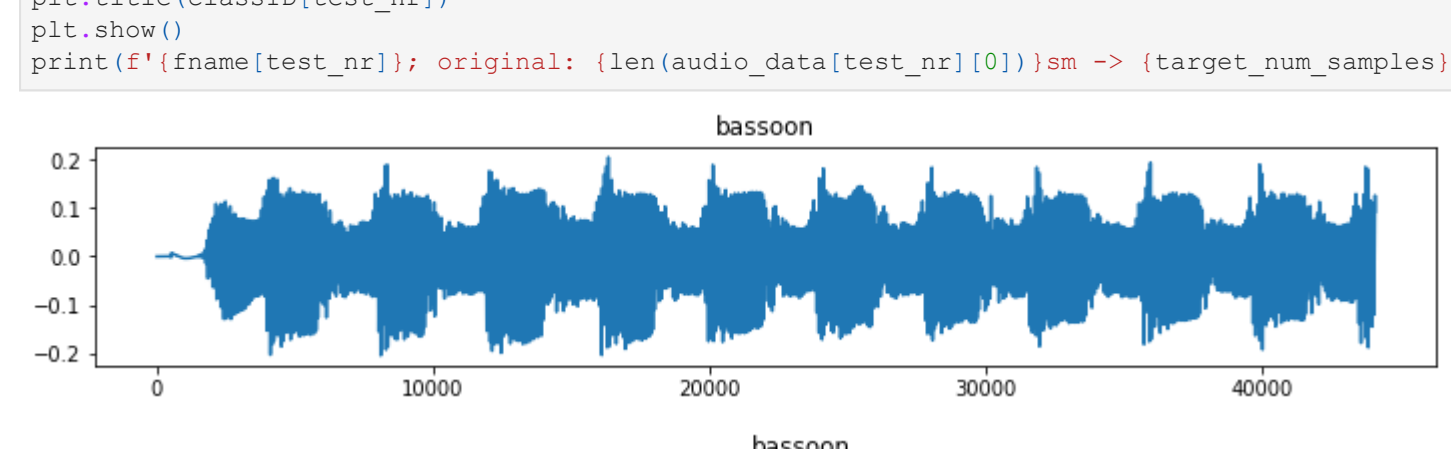
In [18]:
```
# Load
# with open('mfcc_features.pickle', 'rb') as f:
#     mfcc_features = pickle.load(f)
```

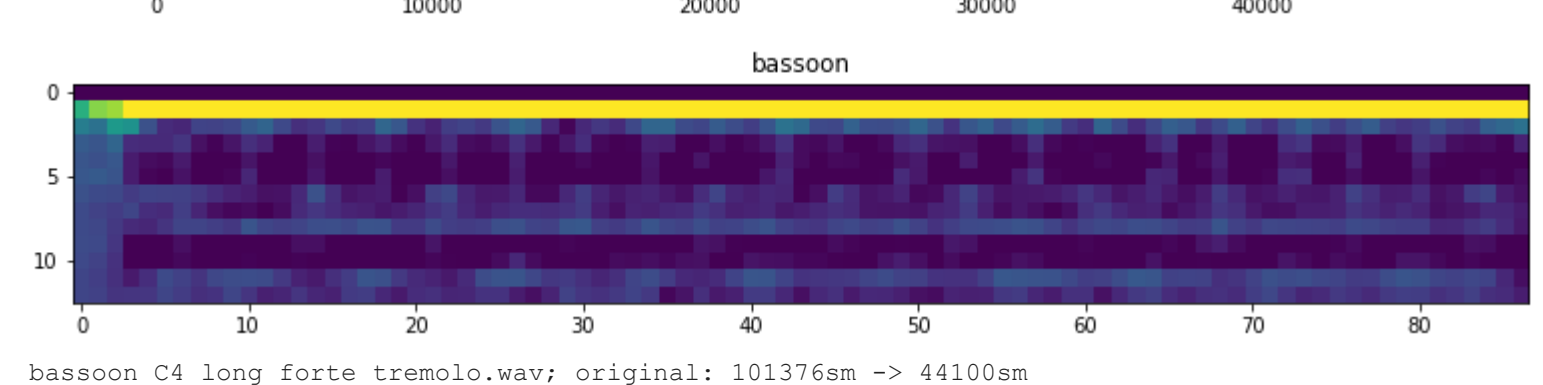
In [19]:
```
print(processed_audio.shape)
print(mfcc_features.shape)
```
```
(13681, 44100)
(13681, 13, 87)
```

Extract and plot a single sound file

ex. shortened file

In [20]:
```
test_nr = 310
plt.figure(figsize=(12,2))
plt.plot(processed_audio[test_nr])
plt.title(f'{classID[test_nr]}')
plt.show()
plt.figure(figsize=(15, 2))
plt.imshow(mfcc_features[test_nr], vmin=0, vmax=1)
plt.title(classID[test_nr])
plt.show()
print(f'{fname[test_nr]}; original: {len(audio_data[test_nr][0])}sm -> {target_num_samples}sm')
```

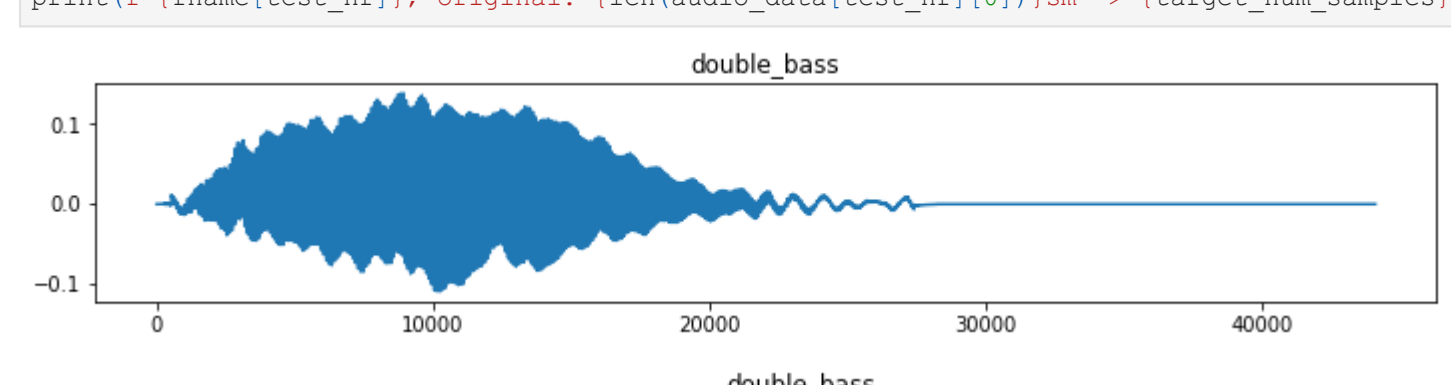


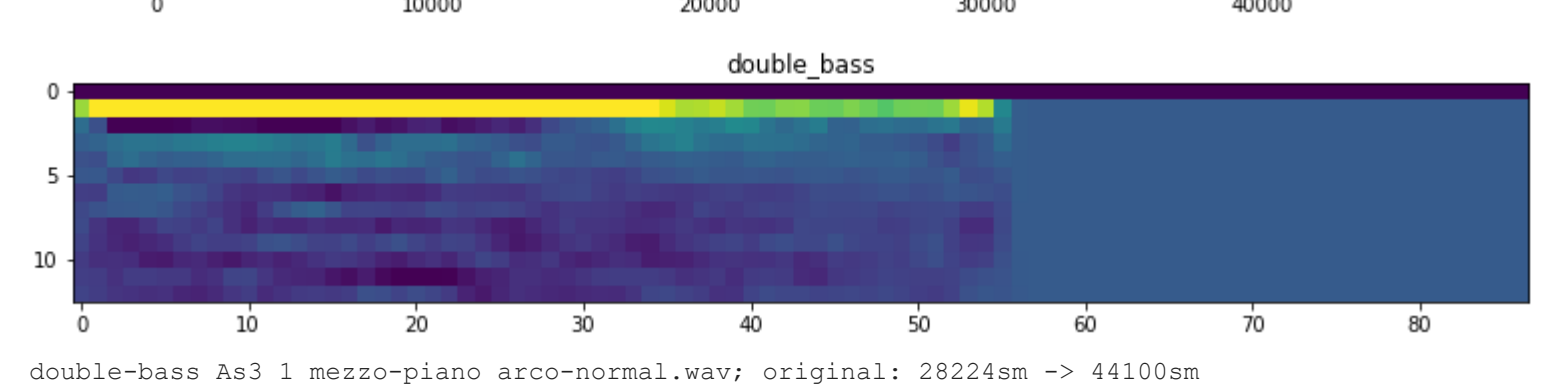



```
bassoon_C4_long_forte_tremolo.wav; original: 101376sm -> 44100sm
```

ex. padded file

In [21]:
```
test_nr = 5001
plt.figure(figsize=(12,2))
plt.plot(processed_audio[test_nr])
plt.title(classID[test_nr])
plt.show()
plt.figure(figsize=(15, 2))
plt.imshow(mfcc_features[test_nr], vmin=0, vmax=1)
plt.title(classID[test_nr])
plt.show()
print(f'{fname[test_nr]}; original: {len(audio_data[test_nr][0])}sm -> {target_num_samples}sm')
```






```
double-bass_As3_1_mezzo-piano_arco-normal.wav; original: 28224sm -> 44100sm
```

Encoding the labels
'banjo' -> '0',
...
'violin' -> '20'
Followed by one-hot-encoding

In [22]:
```
label_encoder = LabelEncoder()
label_encoded = label_encoder.fit_transform(classID)
label_encoded = label_encoded[:, np.newaxis]
```

In [23]:
```
one_hot_encoder = OneHotEncoder(sparse=False)
one_hot_encoded = one_hot_encoder.fit_transform(label_encoded)
```

Create train and test sets

Intuitive labelling for data, normalization of features, stratified splitting to account for the inbalances in the dataset

In [24]:
```
X = mfcc_features
y = one_hot_encoded
X = (X-X.min())/(X.max()-X.min()) # Normalization
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    stratify=y,
                                                    test_size=0.2,
                                                    shuffle=True,
                                                    random_state=8)

X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,
                                                  stratify=y_train,
                                                  test_size=0.25,
                                                  shuffle=True,
                                                  random_state= 8)
```

In [25]:
```
input_shape = (X_train.shape[1], X_train.shape[2], 1)
```

In [26]:
```
input_shape
```
Out[26]:
```
(13, 87, 1)
```

In [27]:
```
# X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], X_train.shape[2], 1)
# X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], X_test.shape[2], 1)

print("X_train shape: {}".format(X_train.shape))
print("X_test shape: {}".format(X_test.shape))
print("y_train shape: {}".format(y_train.shape))
print("y_test shape: {}".format(y_test.shape))
print("X_val shape: {}".format(y_train.shape))
print("y_val shape: {}".format(y_test.shape))
```
```
X_train shape: (8208, 13, 87)
X_test shape: (2737, 13, 87)
y_train shape: (8208, 20)
y_test shape: (2737, 20)
X_val shape: (8208, 20)
y_val shape: (2737, 20)
```

Training

In [28]:
```
# Training parameters

num_epochs = 100
# num_steps = 1000
activation = 'relu'
last_act = 'Softmax'
kernel_init = 'he_normal'
dense_init = keras.initializers.HeNormal()
regularizer = l2(0.01)
padding = 'same'
loss = 'categorical_crossentropy'
optimizer = 'adam'
metrics = 'acc'
filter_dim = (3, 3)

# Early stopping parameters
callback = keras.callbacks.EarlyStopping(monitor='loss', patience=3)
```

CNN Architecture

In [29]:
```
model = Sequential()
model.add(Conv2D(16, filter_dim, activation=activation, strides=(1, 1), padding=padding, input_shape=input_shap
# model.add(MaxPool2D((2, 2), padding=padding))

model.add(Conv2D(32, filter_dim, activation=activation, strides=(1, 1), padding=padding, kernel_initializer=ker
# model.add(MaxPool2D((2, 2), padding=padding))

model.add(Conv2D(64, filter_dim, activation=activation, strides=(1, 1), padding=padding, kernel_initializer=ker
model.add(MaxPool2D((2, 2), padding=padding))

model.add(Conv2D(128, filter_dim, activation=activation, strides=(1, 1), padding=padding, kernel_initializer=ke
model.add(MaxPool2D((2, 2), padding=padding))

model.add(Flatten())
model.add(Dense(512, activation=activation, kernel_initializer=dense_init, kernel_regularizer=regularizer))
model.add(Dropout(0.3))
model.add(Dense(1024, activation=activation, kernel_initializer=dense_init, kernel_regularizer=regularizer))
model.add(Dropout(0.2))
model.add(Dense(512, activation=activation, kernel_initializer=dense_init, kernel_regularizer=regularizer))
model.add(Dense(20, activation=last_act))

model.compile(loss=loss, optimizer=optimizer, metrics=[metrics])
```

In [30]:
```
model.summary()
```
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 13, 87, 16)        160

 conv2d_1 (Conv2D)           (None, 13, 87, 32)        4640

 conv2d_2 (Conv2D)           (None, 13, 87, 64)        18496

 max_pooling2d (MaxPooling2D  (None, 7, 44, 64)        0
 )

 conv2d_3 (Conv2D)           (None, 7, 44, 128)        73856

 max_pooling2d_1 (MaxPooling  (None, 4, 22, 128)       0
 2D)

 flatten (Flatten)           (None, 11264)             0

 dense (Dense)               (None, 512)               5767680

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 1024)              525312

 dropout_1 (Dropout)         (None, 1024)              0

 dense_2 (Dense)             (None, 512)               524800

 dense_3 (Dense)             (None, 20)                10260

=================================================================
Total params: 6,925,204
Trainable params: 6,925,204
Non-trainable params: 0
_________________________________________________________________
```

Train

In [31]:
```
history = model.fit(X_train, y_train,
                    # steps_per_epoch=num_steps,
                    initial_epoch=0,
                    epochs=num_epochs,
                    validation_data=(X_val, y_val),
                    shuffle=True,
                    callbacks=[callback])
```
```
Epoch 1/100
257/257 [==============================] - 15s 40ms/step - loss: 11.3621 - acc: 0.1098 - val_loss: 3.8793 - val_acc: 0.1480
Epoch 2/100
257/257 [==============================] - 9s 36ms/step - loss: 2.9051 - acc: 0.2880 - val_loss: 2.1198 - val_acc: 0.4547
Epoch 3/100
257/257 [==============================] - 9s 36ms/step - loss: 1.9303 - acc: 0.4934 - val_loss: 1.4896 - val_acc: 0.6546
Epoch 4/100
257/257 [==============================] - 9s 37ms/step - loss: 1.5381 - acc: 0.6390 - val_loss: 1.2171 - val_acc: 0.7588
Epoch 5/100
257/257 [==============================] - 9s 36ms/step - loss: 1.3293 - acc: 0.7105 - val_loss: 1.0379 - val_acc: 0.8118
Epoch 6/100
257/257 [==============================] - 9s 36ms/step - loss: 1.1593 - acc: 0.7682 - val_loss: 1.0530 - val_acc: 0.8067
Epoch 7/100
257/257 [==============================] - 9s 36ms/step - loss: 1.0468 - acc: 0.8036 - val_loss: 0.9467 - val_acc: 0.8443
Epoch 8/100
257/257 [==============================] - 9s 36ms/step - loss: 0.9458 - acc: 0.8366 - val_loss: 0.8623 - val_acc: 0.8655
Epoch 9/100
257/257 [==============================] - 9s 36ms/step - loss: 0.9236 - acc: 0.8447 - val_loss: 0.8179 - val_acc: 0.8798
Epoch 10/100
257/257 [==============================] - 9s 36ms/step - loss: 0.8445 - acc: 0.8625 - val_loss: 0.7809 - val_acc: 0.8776
Epoch 11/100
257/257 [==============================] - 9s 36ms/step - loss: 0.8048 - acc: 0.8739 - val_loss: 0.7707 - val_acc: 0.8904
Epoch 12/100
257/257 [==============================] - 9s 36ms/step - loss: 0.7949 - acc: 0.8777 - val_loss: 0.7364 - val_acc: 0.8966
Epoch 13/100
257/257 [==============================] - 9s 36ms/step - loss: 0.7481 - acc: 0.8904 - val_loss: 0.6857 - val_acc: 0.9108
Epoch 14/100
257/257 [==============================] - 9s 36ms/step - loss: 0.7356 - acc: 0.8938 - val_loss: 0.6751 - val_acc: 0.9156
Epoch 15/100
257/257 [==============================] - 9s 37ms/step - loss: 0.7301 - acc: 0.8927 - val_loss: 0.6379 - val_acc: 0.9221
Epoch 16/100
257/257 [==============================] - 9s 37ms/step - loss: 0.7359 - acc: 0.8949 - val_loss: 0.6413 - val_acc: 0.9192
Epoch 17/100
257/257 [==============================] - 9s 37ms/step - loss: 0.6862 - acc: 0.9051 - val_loss: 0.6603 - val_acc: 0.9148
Epoch 18/100
257/257 [==============================] - 9s 36ms/step - loss: 0.6609 - acc: 0.9074 - val_loss: 0.6568 - val_acc: 0.9112
Epoch 19/100
257/257 [==============================] - 9s 36ms/step - loss: 0.6552 - acc: 0.9136 - val_loss: 0.7485 - val_acc: 0.8929
Epoch 20/100
257/257 [==============================] - 9s 36ms/step - loss: 0.6543 - acc: 0.9137 - val_loss: 0.6161 - val_acc: 0.9327
Epoch 21/100
257/257 [==============================] - 9s 36ms/step - loss: 0.6386 - acc: 0.9231 - val_loss: 0.6230 - val_acc: 0.9240
Epoch 22/100
257/257 [==============================] - 9s 36ms/step - loss: 0.6389 - acc: 0.9161 - val_loss: 0.6537 - val_acc: 0.9152
Epoch 23/100
257/257 [==============================] - 9s 36ms/step - loss: 0.6309 - acc: 0.9213 - val_loss: 0.6335 - val_acc: 0.9207
Epoch 24/100
257/257 [==============================] - 9s 37ms/step - loss: 0.6186 - acc: 0.9221 - val_loss: 0.6239 - val_acc: 0.9221
Epoch 25/100
257/257 [==============================] - 10s 37ms/step - loss: 0.5902 - acc: 0.9288 - val_loss: 0.5961 - val_acc: 0.9324
Epoch 26/100
257/257 [==============================] - 9s 37ms/step - loss: 0.6079 - acc: 0.9257 - val_loss: 0.6675 - val_acc: 0.9101
Epoch 27/100
257/257 [==============================] - 9s 36ms/step - loss: 0.5634 - acc: 0.9332 - val_loss: 0.5687 - val_acc: 0.9302
Epoch 28/100
257/257 [==============================] - 9s 37ms/step - loss: 0.5774 - acc: 0.9321 - val_loss: 0.5757 - val_acc: 0.9335
Epoch 29/100
257/257 [==============================] - 9s 37ms/step - loss: 0.5821 - acc: 0.9288 - val_loss: 0.5486 - val_acc: 0.9448
Epoch 30/100
257/257 [==============================] - 9s 37ms/step - loss: 0.5630 - acc: 0.9330 - val_loss: 0.5533 - val_acc: 0.9379
Epoch 31/100
257/257 [==============================] - 9s 36ms/step - loss: 0.5734 - acc: 0.9358 - val_loss: 0.6075 - val_acc: 0.9327
Epoch 32/100
257/257 [==============================] - 9s 36ms/step - loss: 0.5486 - acc: 0.9388 - val_loss: 0.5854 - val_acc: 0.9349
Epoch 33/100
257/257 [==============================] - 9s 36ms/step - loss: 0.5402 - acc: 0.9423 - val_loss: 0.5576 - val_acc: 0.9364
Epoch 34/100
257/257 [==============================] - 9s 36ms/step - loss: 0.5744 - acc: 0.9365 - val_loss: 0.5908 - val_acc: 0.9349
Epoch 35/100
257/257 [==============================] - 9s 36ms/step - loss: 0.5547 - acc: 0.9375 - val_loss: 0.5473 - val_acc: 0.9364
Epoch 36/100
257/257 [==============================] - 9s 37ms/step - loss: 0.5711 - acc: 0.9357 - val_loss: 0.5702 - val_acc: 0.9368
```

Save/load the model

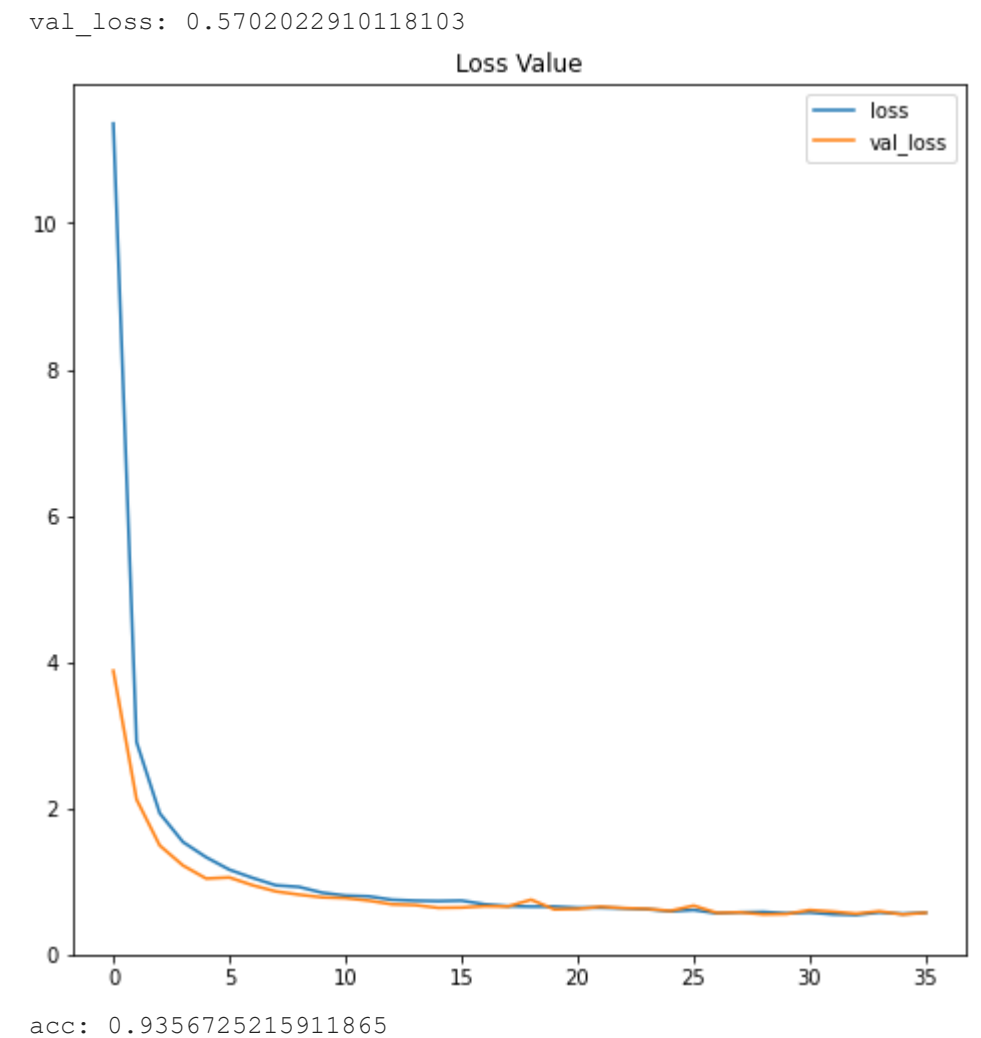
In [32]:
```
model.save("cnn_philharmonia.h5")
#model = keras.models.load_model("cnn_philharmonia.h5")
```

Export model.json and *.bins with weights

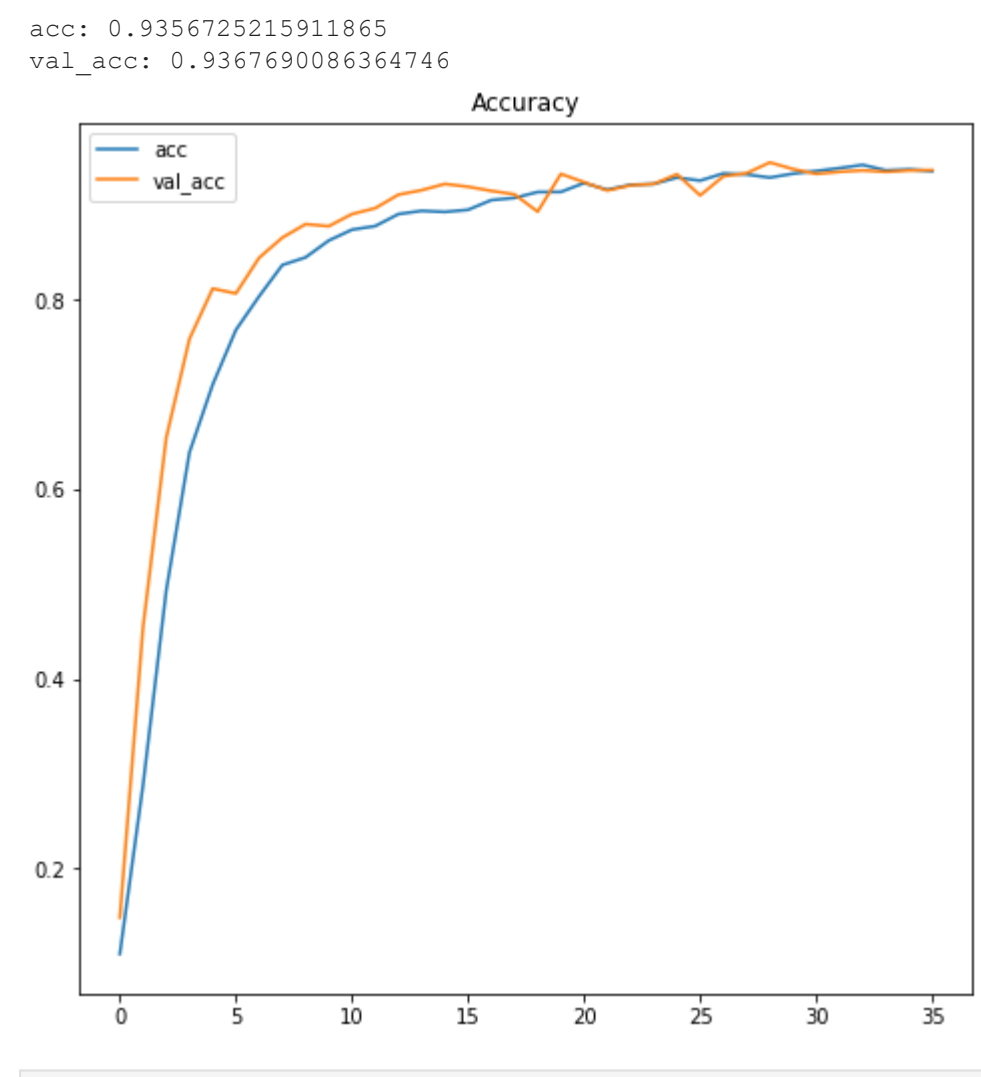
In [33]:
```
!tensorflowjs_converter --input_format keras "cnn_philharmonia.h5" ./jsmodel
```

Evaluation

In [34]:
```
plt.figure(figsize=(8,8))
plt.title('Loss Value')
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['loss', 'val_loss'])
print('loss', history.history['loss'][-1])
print('val_loss:', history.history['val_loss'][-1])
plt.show()
plt.figure(figsize=(8,8))
plt.title('Accuracy')
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.legend(['acc', 'val_acc'])
print('acc:', history.history['acc'][-1])
print('val_acc:', history.history['val_acc'][-1])
plt.show()
```
```
loss 0.5710670948028564
val_loss: 0.5702022910118103
```



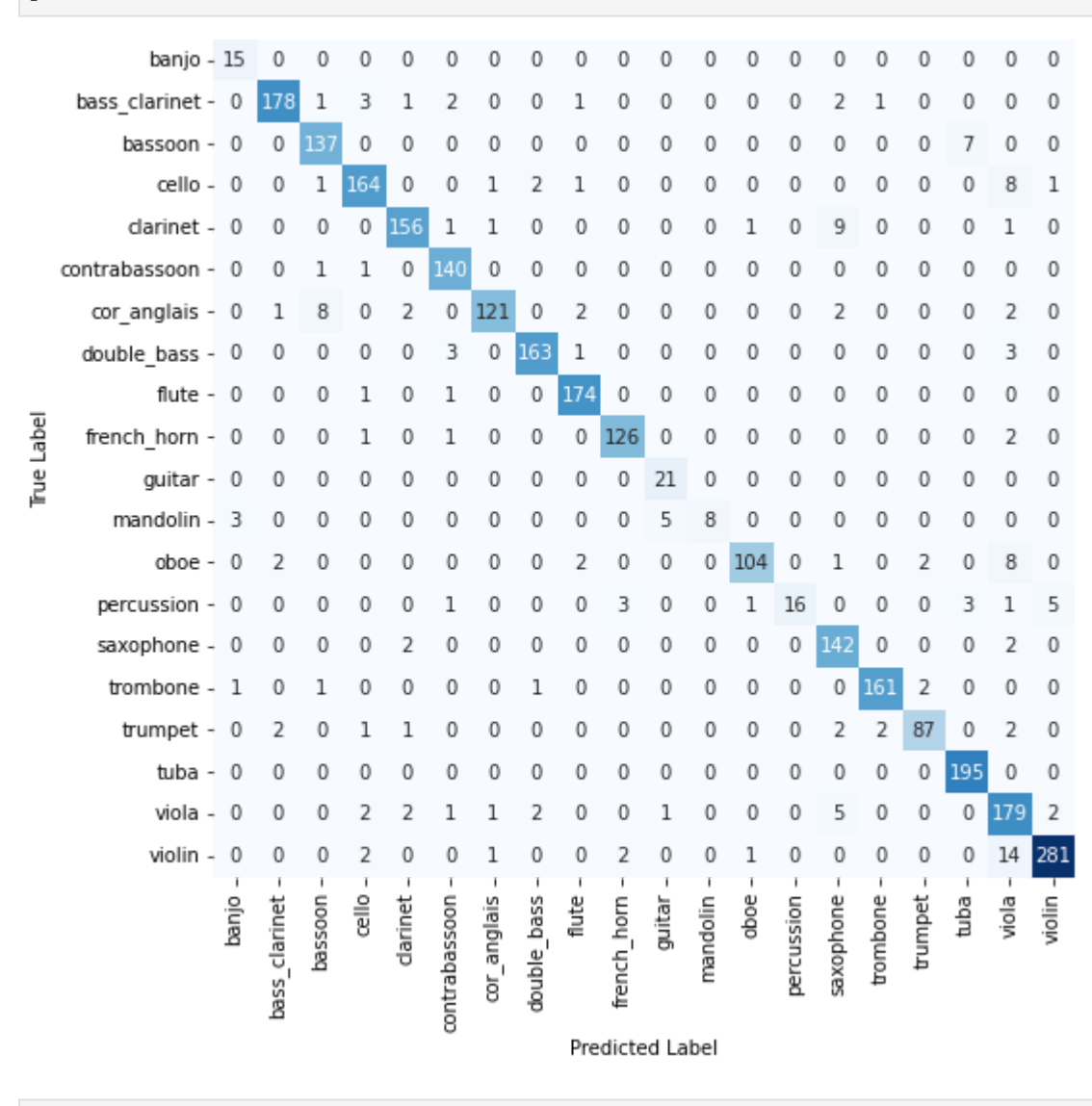

```
acc: 0.9356725215911865
val_acc: 0.9367690086364746
```



In [35]:
```
predictions = model.predict(X_test)
```
```
86/86 [==============================] - 1s 9ms/step
```

In [36]:
```
predictions = np.argmax(predictions, axis=1)
y_test = one_hot_encoder.inverse_transform(y_test)
```

In [37]:
```
cm = confusion_matrix(y_test, predictions)
plt.figure(figsize=(8,8))
sns.heatmap(cm, annot=True, xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_, fmt='d', cm
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



In [38]:
```
# Classification report
print("\nClassification report:\n", classification_report(y_test, predictions, target_names=folders))
```
```
Classification report:
               precision    recall  f1-score   support

        banjo       0.79      1.00      0.88        15
      bassoon       0.97      0.94      0.96       189
bass_clarinet       0.92      0.95      0.94       144
        cello       0.94      0.92      0.93       178
     clarinet       0.95      0.92      0.94       169
contrabassoon       0.93      0.99      0.96       142
  cor_anglais       0.97      0.88      0.92       138
  double_bass       0.97      0.96      0.96       170
        flute       0.96      0.99      0.97       176
  french_horn       0.96      0.97      0.97       130
       guitar       0.78      1.00      0.88        21
     mandolin       1.00      0.50      0.67        16
         oboe       0.97      0.87      0.92       119
   percussion       1.00      0.53      0.70        30
    saxophone       0.87      0.97      0.92       146
     trombone       0.98      0.97      0.98       166
      trumpet       0.96      0.90      0.93        97
         tuba       0.95      1.00      0.97       195
        viola       0.81      0.92      0.86       195
       violin       0.97      0.93      0.95       301

     accuracy                           0.94      2737
    macro avg       0.93      0.91      0.91      2737
 weighted avg       0.94      0.94      0.94      2737
```