# openmic-MEL-DL

## March 2, 2020

```
[1]: import librosa as lb
   import librosa.display
   import scipy
   import ison
   import numpy as np
   import sklearn
   from sklearn.metrics import classification_report
   from sklearn.model_selection import train_test_split
   import os
   import keras
   from keras.utils import np_utils
   from keras import layers
   from keras import models
   from keras.models import Sequential
   from keras.layers import Dense, Conv2D, MaxPool2D, Flatten, Dropout
   from keras.preprocessing.image import ImageDataGenerator
   from model_builder import build_example
   from plotter import plot_history
   import matplotlib.pyplot as plt
```

Using TensorFlow backend.

```
[2]: # CONSTANTS

DATA_DIR = "openmic-2018/"
CATEGORY_COUNT = 8
   LEARNING_RATE = 0.00001
   THRESHOLD = 0.5

[]: # MEL-SPECTOGRAM EXAMPLE

   y, sr = lb.load(DATA_DIR + 'audio/000/000135_483840.ogg')
   S = lb.feature.melspectrogram(y=y, sr=sr)

S_dB = lb.power_to_db(S, ref=0) # 10 * log10(S / ref)
```

```
print(y.shape)
   print(sr)
   print(S.shape)
   print(S_dB.shape)
   librosa.display.specshow(S_dB, x_axis='s', y_axis='mel')
   plt.colorbar(format='%+2.0f dB')
[]: MEL = []
   sum = 0
   for i in range(X.shape[0]):
       key = sample key[i]
       key pref = key[:3]
       y, sr = lb.load(DATA_DIR + 'audio/' + key_pref + '/' + key + '.ogg')
       S = lb.feature.melspectrogram(y=y, sr=sr)
       S_dB = lb.power_to_db(S, ref=0)
       MEL.append(S_dB[:,:430])
[]: MEL S = np.asarray(MEL)
   print('Mel has shape: ' + str(MEL_S.shape))
[]: # TODO SAVE WITHOUT X
   np.savez('openmic-test-delete.npz', MEL = X, Y_true=Y_true, Y_mask=Y_mask,__
    →sample_key=sample_key)
[]: np.savez_compressed('openmic-mel-only.npz', MEL = MEL_S)
   print('OpenMIC keys: ' + str(list(OPENMIC 2.keys())))
[3]: OPENMIC_2 = np.load(os.path.join(DATA_DIR, 'openmic-mel.npz'),
    →allow_pickle=True)
   X, Y_true, Y_mask, sample_key = OPENMIC_2['MEL'], OPENMIC_2['Y_true'],
    →OPENMIC_2['Y_mask'], OPENMIC_2['sample_key']
[]: # LOAD DATA
   OPENMIC = np.load(os.path.join(DATA DIR, 'openmic-2018.npz'), allow pickle=True)
   print('OpenMIC keys: ' + str(list(OPENMIC.keys())))
   X, Y_true, Y_mask, sample_key = OPENMIC['X'], OPENMIC['Y_true'],
    →OPENMIC['Y_mask'], OPENMIC['sample_key']
   print('X has shape: ' + str(X.shape))
   print('Y_true has shape: ' + str(Y_true.shape))
   print('Y_mask has shape: ' + str(Y_mask.shape))
   print('sample_key has shape: ' + str(sample_key.shape))
[4]: # LOAD LABELS
   with open(os.path.join(DATA_DIR, 'class-map.json'), 'r') as f:
       INSTRUMENTS = json.load(f)
```

```
print('OpenMIC instruments: ' + str(INSTRUMENTS))
    OpenMIC instruments: {'accordion': 0, 'banjo': 1, 'bass': 2, 'cello': 3,
    'clarinet': 4, 'cymbals': 5, 'drums': 6, 'flute': 7, 'guitar': 8,
    'mallet_percussion': 9, 'mandolin': 10, 'organ': 11, 'piano': 12, 'saxophone':
    13, 'synthesizer': 14, 'trombone': 15, 'trumpet': 16, 'ukulele': 17, 'violin':
    18, 'voice': 19}
 [5]: # SPLIT DATA (TRAIN - TEST - VAL)
     # CHANGE X TO MEL
     split_train, split_test, X_train, X_test, Y_true_train, Y_true_test, U_

¬Y_mask_train, Y_mask_test = train_test_split(sample_key, X, Y_true, Y_mask)
     split_val, split_test, X_val, X_test, Y_true_val, Y_true_test, Y_mask_val,_
     →Y_mask_test = train_test_split(split_test, X_test, Y_true_test, Y_mask_test, U_
     \rightarrowtest_size=0.5)
     train_set = np.asarray(set(split_train))
     test set = np.asarray(set(split test))
     print('# Train: {}, # Val: {}, # Test: {}'.format(len(split_train),_
      →len(split_test), len(split_val)))
    # Train: 15000, # Val: 2500, # Test: 2500
[34]: # DUPLICATE OF THE MODEL PREPROCESS
     print(X_train.shape)
     print(X_test.shape)
     for instrument in INSTRUMENTS:
         # Map the instrument name to its column number
         inst num = INSTRUMENTS[instrument]
         print(instrument)
         # TRAIN
         train_inst = Y_mask_train[:, inst_num]
         X_train_inst = X_train[train_inst]
         X_train_inst = X_train_inst.astype('float16')
         shape = X_train_inst.shape
         X_train inst = X_train inst.reshape(shape[0],1, shape[1], shape[2])
         Y_true_train_inst = Y_true_train[train_inst, inst_num] >= THRESHOLD
         for val in Y_true_train_inst:
             i += val
```

```
print('TRAIN: ' + str(i) + ' true of ' + str(len(Y_true_train_inst)) + ' ('__
 →+ str(round(i / len(Y_true_train_inst ) * 100,2)) + ' %)')
    # TEST
    test inst = Y mask test[:, inst num]
    X_test_inst = X_test[test_inst]
    X_test_inst = X_test_inst.astype('float16')
    shape = X_test_inst.shape
    X_test_inst = X_test_inst.reshape(shape[0],1, shape[1], shape[2])
    Y_true_test_inst = Y_true_test[test_inst, inst_num] >= THRESHOLD
    i = 0
    for val in Y_true_test_inst:
        i += val
    print('TEST: ' + str(i) + ' true of ' + str(len(Y_true_test_inst)) + ' (' + "
 →str(round(i / len(Y_true_test_inst ) * 100,2)) + ' %)')
    # VALIDATION
    val_inst = Y_mask_val[:, inst_num]
    X_val_inst = X_val[val_inst]
    X_val_inst = X_val_inst.astype('float16')
    shape = X_val_inst.shape
    X_val_inst = X_val_inst.reshape(shape[0],1, shape[1], shape[2])
    Y true val inst = Y true val[val inst, inst num] >= THRESHOLD
    i = 0
    for val in Y_true_val_inst:
        i += val
    print('VALIDATION: ' + str(i) + ' true of ' + str(len(Y_true_val_inst)) + '__
 \rightarrow (' + str(round(i / len(Y true val inst ) * 100,2)) + ' %)')
(15000, 128, 430)
(2500, 128, 430)
accordion
TRAIN: 367 true of 1540 (23.83 %)
TEST: 64 true of 279 (22.94 %)
VALIDATION: 58 true of 252 (23.02 %)
banjo
TRAIN: 532 true of 1620 (32.84 %)
TEST: 99 true of 307 (32.25 %)
VALIDATION: 101 true of 291 (34.71 %)
bass
TRAIN: 410 true of 1401 (29.26 %)
```

TEST: 65 true of 234 (27.78 %)

VALIDATION: 74 true of 253 (29.25 %)

cello

TRAIN: 643 true of 1490 (43.15 %)

TEST: 97 true of 243 (39.92 %)

VALIDATION: 84 true of 216 (38.89 %)

clarinet

TRAIN: 411 true of 1810 (22.71 %)

TEST: 59 true of 293 (20.14 %)

VALIDATION: 63 true of 282 (22.34 %)

cymbals

TRAIN: 816 true of 1280 (63.75 %)

TEST: 144 true of 225 (64.0 %)

VALIDATION: 151 true of 230 (65.65 %)

drums

TRAIN: 827 true of 1313 (62.99 %)

TEST: 144 true of 226 (63.72 %)

VALIDATION: 135 true of 208 (64.9 %)

flute

TRAIN: 484 true of 1562 (30.99 %)

TEST: 82 true of 277 (29.6 %)

VALIDATION: 81 true of 245 (33.06 %)

guitar

TRAIN: 859 true of 1232 (69.72 %)

TEST: 147 true of 215 (68.37 %)

VALIDATION: 132 true of 203 (65.02 %)

mallet\_percussion

TRAIN: 561 true of 1393 (40.27 %)

TEST: 67 true of 191 (35.08 %)

VALIDATION: 105 true of 218 (48.17 %)

mandolin

TRAIN: 619 true of 1799 (34.41 %)

TEST: 107 true of 314 (34.08 %)

VALIDATION: 119 true of 351 (33.9 %)

organ

TRAIN: 454 true of 1427 (31.81 %)

TEST: 65 true of 224 (29.02 %)

VALIDATION: 84 true of 239 (35.15 %)

piano

TRAIN: 871 true of 1284 (67.83 %)

TEST: 164 true of 237 (69.2 %)

VALIDATION: 135 true of 199 (67.84 %)

saxophone

TRAIN: 841 true of 1769 (47.54 %)

TEST: 141 true of 286 (49.3 %)

VALIDATION: 153 true of 310 (49.35 %)

synthesizer

TRAIN: 798 true of 1178 (67.74 %)

```
TEST: 146 true of 225 (64.89 %)
    VALIDATION: 147 true of 199 (73.87 %)
    trombone
    TRAIN: 653 true of 2058 (31.73 %)
    TEST: 110 true of 362 (30.39 %)
    VALIDATION: 100 true of 340 (29.41 %)
    trumpet
    TRAIN: 861 true of 2179 (39.51 %)
    TEST: 145 true of 385 (37.66 %)
    VALIDATION: 140 true of 352 (39.77 %)
    ukulele
    TRAIN: 542 true of 1805 (30.03 %)
    TEST: 90 true of 298 (30.2 %)
    VALIDATION: 106 true of 322 (32.92 %)
    TRAIN: 884 true of 1529 (57.82 %)
    TEST: 138 true of 244 (56.56 %)
    VALIDATION: 151 true of 260 (58.08 %)
    voice
    TRAIN: 752 true of 1174 (64.05 %)
    TEST: 126 true of 197 (63.96 %)
    VALIDATION: 110 true of 193 (56.99 %)
[15]: # VALAMI FANCY ADATKIÍRÁS
     len(Y_true_val_inst)
[15]: 193
 [9]: # This dictionary will include the classifiers for each model
     mymodels = dict()
     # We'll iterate over all istrument classes, and fit a model for each one
     # After training, we'll print a classification report for each instrument
     for instrument in INSTRUMENTS:
         # Map the instrument name to its column number
         inst_num = INSTRUMENTS[instrument]
         # Step 1: sub-sample the data
         # First, we need to select down to the data for which we have annotations
         # This is what the mask arrays are for
         # Here, we're using the Y_mask_train array to slice out only the training_
      \rightarrow examples
         # for which we have annotations for the given class
         # Again, we slice the labels to the annotated examples
         # We thresold the label likelihoods at 0.5 to get binary labels
         train_inst = Y_mask_train[:, inst_num]
```

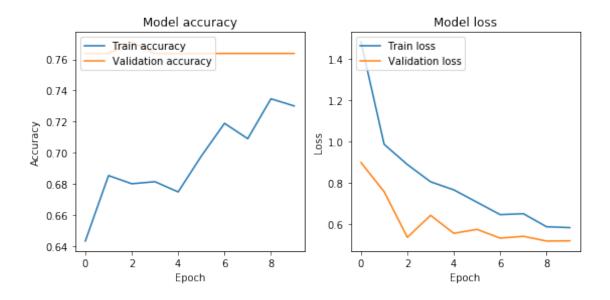
```
X_train_inst = X_train[train_inst]
  X_train_inst = X_train_inst.astype('float16')
  shape = X_train_inst.shape
  X_train_inst = X_train_inst.reshape(shape[0],1, shape[1], shape[2])
  Y_true_train_inst = Y_true_train[train_inst, inst_num] >= THRESHOLD
  # TEST
  test_inst = Y_mask_test[:, inst_num]
  X_test_inst = X_test[test_inst]
  X_test_inst = X_test_inst.astype('float16')
  shape = X_test_inst.shape
  X_test_inst = X_test_inst.reshape(shape[0],1, shape[1], shape[2])
  Y_true_test_inst = Y_true_test[test_inst, inst_num] >= THRESHOLD
  # VALIDATION
  val_inst = Y_mask_val[:, inst_num]
  X_val_inst = X_val[val_inst]
  X_val_inst = X_val_inst.astype('float16')
  shape = X_val_inst.shape
  X_val_inst = X_val_inst.reshape(shape[0],1, shape[1], shape[2])
  Y_true_val_inst = Y_true_val[val_inst, inst_num] >= THRESHOLD
  # Step 3.
  # Initialize a new classifier
  model = models.Sequential()
  model.
→add(Conv2D(input_shape=(1,128,430),data_format="channels_first",filters=32,kernel_size=(3,3
→activation="relu"))
  model.add(Conv2D(filters=32,kernel_size=(3,3),padding="same",u
→activation="relu"))
  model.add(MaxPool2D(pool_size=(3,3),strides=(2,2)))
  model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same",_
→activation="relu"))
  model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", __
→activation="relu"))
  model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))
  model.add(Dropout(0.2))
  model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same",_
→activation="relu"))
  model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))
  model.add(layers.Flatten())
  model.add(layers.Dense(units=256, activation='relu'))
  model.add(layers.Dense(units=1, activation='sigmoid'))
  model.compile(loss='binary_crossentropy', optimizer=keras.optimizers.
→Adam(lr= LEARNING_RATE), metrics = ['accuracy'])
```

```
# model.summary()
    # Step 4.
    history = model.fit(X_train_inst,Y_true_train_inst , epochs=10,_
 →batch_size=64, validation_data=(X_val_inst,Y_true_val_inst))
    plot_history()
    loss, acc = model.evaluate(X_test_inst, Y_true_test_inst)
    print('Test loss: {}'.format(loss))
    print('Test accuracy: {:.2%}'.format(acc))
    # Step 5.
    # Finally, we'll evaluate the model on both train and test
    Y_pred_train = model.predict(X_train_inst)
    Y_pred_test = model.predict(X_test_inst)
    Y_pred_train_bool = Y_pred_train > THRESHOLD - 0.15 #THRESHOLD (should be_
 \rightarrow lower than 0.5)
    Y_pred_test_bool = Y_pred_test > THRESHOLD - 0.15 #THRESHOLD (should be_
 \rightarrow lower than 0.5)
    print('-' * 52)
    print(instrument)
    print('\tTRAIN')
    print(classification_report(Y_true_train_inst, Y_pred_train_bool))
    print('\tTEST')
    print(classification_report(Y_true_test_inst, Y_pred_test_bool))
     # Store the classifier in our dictionary
mymodels[instrument] = model
WARNING:tensorflow:From C:\Users\user\Anaconda3\lib\site-
```

```
packages\tensorflow\python\framework\op_def_library.py:263: colocate_with (from
tensorflow.python.framework.ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From C:\Users\user\Anaconda3\lib\site-
packages\keras\backend\tensorflow_backend.py:3733: calling dropout (from
tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed
in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 -
keep prob`.
WARNING:tensorflow:From C:\Users\user\Anaconda3\lib\site-
packages\tensorflow\python\ops\math_ops.py:3066: to_int32 (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a future
version.
```

Instructions for updating:

```
Use tf.cast instead.
Train on 1519 samples, validate on 271 samples
Epoch 1/10
acc: 0.6432 - val_loss: 0.8994 - val_acc: 0.7638
Epoch 2/10
acc: 0.6853 - val_loss: 0.7584 - val_acc: 0.7638
Epoch 3/10
acc: 0.6801 - val_loss: 0.5379 - val_acc: 0.7712
acc: 0.6814 - val_loss: 0.6440 - val_acc: 0.7638
acc: 0.6748 - val_loss: 0.5574 - val_acc: 0.7638
Epoch 6/10
acc: 0.6978 - val_loss: 0.5762 - val_acc: 0.7638
acc: 0.7189 - val_loss: 0.5339 - val_acc: 0.7638
Epoch 8/10
acc: 0.7090 - val_loss: 0.5428 - val_acc: 0.7638
Epoch 9/10
acc: 0.7347 - val_loss: 0.5197 - val_acc: 0.7638
Epoch 10/10
acc: 0.7301 - val_loss: 0.5208 - val_acc: 0.7638
```



281/281 [======== ] - 17s 61ms/step

Test loss: 0.5738391290780064

Test accuracy: 75.09%

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accordion

TRATN

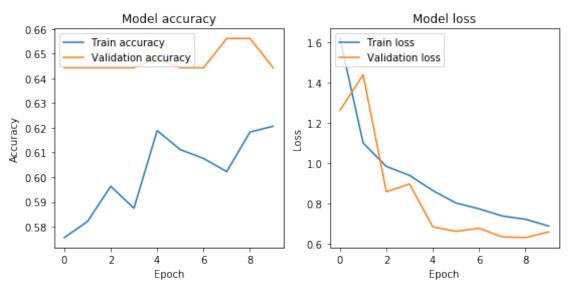
IRAIN					
	precision	recall	f1-score	support	
False	0.77	0.98	0.86	1164	
True	0.47	0.07	0.12	355	
			0.70	4540	
accuracy			0.76	1519	
macro avg	0.62	0.52	0.49	1519	
weighted avg	0.70	0.76	0.69	1519	
TEST					
1501					
	precision	recall	f1-score	support	
False	0.75	0.97	0.85	211	
True	0.30	0.04	0.07	70	
accuracy			0.74	281	
macro avg	0.53	0.50	0.46	281	
weighted avg	0.64	0.74	0.65	281	

Train on 1687 samples, validate on 253 samples

Epoch 1/10

acc: 0.5756 - val\_loss: 1.2620 - val\_acc: 0.6443

```
Epoch 2/10
acc: 0.5821 - val_loss: 1.4386 - val_acc: 0.6443
Epoch 3/10
acc: 0.5963 - val_loss: 0.8577 - val_acc: 0.6443
Epoch 4/10
acc: 0.5874 - val_loss: 0.8959 - val_acc: 0.6443
Epoch 5/10
acc: 0.6189 - val_loss: 0.6830 - val_acc: 0.6482
Epoch 6/10
acc: 0.6111 - val_loss: 0.6609 - val_acc: 0.6443
Epoch 7/10
acc: 0.6076 - val_loss: 0.6761 - val_acc: 0.6443
Epoch 8/10
acc: 0.6023 - val_loss: 0.6332 - val_acc: 0.6561
Epoch 9/10
acc: 0.6183 - val_loss: 0.6299 - val_acc: 0.6561
Epoch 10/10
acc: 0.6206 - val_loss: 0.6582 - val_acc: 0.6443
```



278/278 [========= ] - 18s 66ms/step

Test loss: 0.6368379172661321

Test accuracy: 66.55%

\_\_\_\_\_

	precision	recall	f1-score	support
False	0.69	0.93	0.79	1138
True	0.48	0.13	0.20	549
accuracy			0.67	1687
macro avg	0.58	0.53	0.50	1687
weighted avg	0.62	0.67	0.60	1687
TEST				
	precision	recall	f1-score	support
False	0.66	0.89	0.76	185
True	0.32	0.11	0.16	93
accuracy			0.63	278
macro avg	0.49	0.50	0.46	278
weighted avg	0.55	0.63	0.56	278

Train on 1416 samples, validate on 224 samples

Epoch 1/10

acc: 0.5798 - val\_loss: 0.6392 - val\_acc: 0.7054

Epoch 2/10

acc: 0.6024 - val\_loss: 0.5599 - val\_acc: 0.7098

Epoch 3/10

acc: 0.6667 - val\_loss: 0.5339 - val\_acc: 0.7411

Epoch 4/10

acc: 0.6638 - val\_loss: 0.5146 - val\_acc: 0.7277

Epoch 5/10

acc: 0.6681 - val\_loss: 0.5047 - val\_acc: 0.7321

Epoch 6/10

acc: 0.6631 - val\_loss: 0.5009 - val\_acc: 0.7143

Epoch 7/10

acc: 0.6758 - val\_loss: 0.4908 - val\_acc: 0.7455

Epoch 8/10

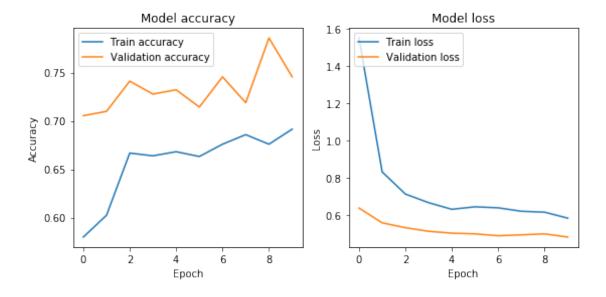
acc: 0.6857 - val\_loss: 0.4957 - val\_acc: 0.7188

Epoch 9/10

acc: 0.6758 - val\_loss: 0.5009 - val\_acc: 0.7857

Epoch 10/10

acc: 0.6914 - val\_loss: 0.4838 - val\_acc: 0.7455



248/248 [========== ] - 15s 62ms/step

Test loss: 0.48448632417186616

Test accuracy: 76.61%

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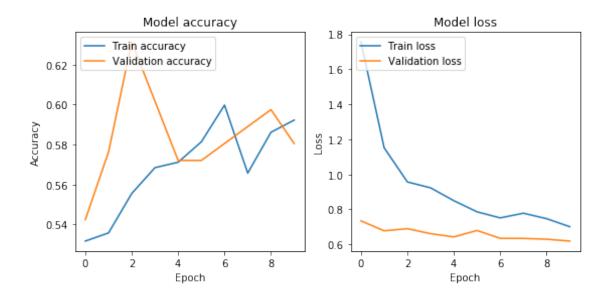
bass

TRAIN				
	precision	recall	f1-score	support
False	0.83	0.71	0.77	1003
True	0.48	0.65	0.55	413
accuracy			0.70	1416
macro avg	0.66	0.68	0.66	1416
weighted avg	0.73	0.70	0.71	1416
TEST				
	precision	recall	f1-score	support
	-			
False	0.89	0.79	0.83	178
True	0.58	0.74	0.65	70

```
0.73 0.76
                   0.74
 macro avg
                         248
weighted avg
         0.80
              0.77
                   0.78
                         248
Train on 1469 samples, validate on 236 samples
Epoch 1/10
acc: 0.5317 - val_loss: 0.7347 - val_acc: 0.5424
Epoch 2/10
acc: 0.5357 - val_loss: 0.6780 - val_acc: 0.5763
acc: 0.5555 - val_loss: 0.6902 - val_acc: 0.6314
1469/1469 [============= ] - 235s 160ms/step - loss: 0.9233 -
acc: 0.5684 - val_loss: 0.6616 - val_acc: 0.6017
Epoch 5/10
acc: 0.5711 - val_loss: 0.6432 - val_acc: 0.5720
Epoch 6/10
acc: 0.5813 - val_loss: 0.6798 - val_acc: 0.5720
Epoch 7/10
acc: 0.5997 - val_loss: 0.6352 - val_acc: 0.5805
Epoch 8/10
acc: 0.5657 - val_loss: 0.6345 - val_acc: 0.5890
Epoch 9/10
acc: 0.5861 - val_loss: 0.6299 - val_acc: 0.5975
Epoch 10/10
acc: 0.5922 - val loss: 0.6194 - val acc: 0.5805
```

0.77

accuracy



244/244 [========= ] - 15s 60ms/step

Test loss: 0.5947532761292379

Test accuracy: 65.16%

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cello

TRAIN

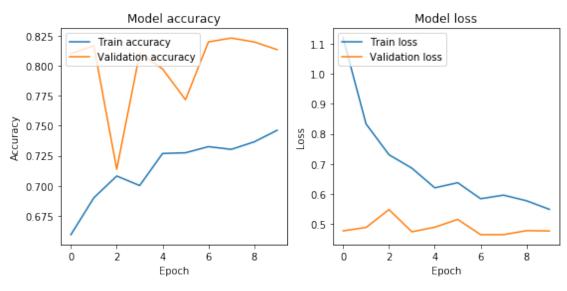
	precision	recall	f1-score	support
False	0.77	0.53	0.63	843
True	0.56	0.79	0.65	626
accuracy			0.64	1469
macro avg	0.66	0.66	0.64	1469
weighted avg	0.68	0.64	0.64	1469
TEST				
	precision	recall	f1-score	support
False	0.83	0.52	0.64	145
True	0.55	0.84	0.66	99
accuracy			0.65	244
macro avg	0.69	0.68	0.65	244
weighted avg	0.71	0.65	0.65	244

Train on 1758 samples, validate on 311 samples

Epoch 1/10

acc: 0.6593 - val\_loss: 0.4773 - val\_acc: 0.8103

```
Epoch 2/10
acc: 0.6900 - val_loss: 0.4884 - val_acc: 0.8167
Epoch 3/10
acc: 0.7082 - val_loss: 0.5479 - val_acc: 0.7138
Epoch 4/10
acc: 0.7002 - val_loss: 0.4740 - val_acc: 0.8103
Epoch 5/10
acc: 0.7270 - val_loss: 0.4893 - val_acc: 0.7974
Epoch 6/10
acc: 0.7275 - val_loss: 0.5152 - val_acc: 0.7717
Epoch 7/10
acc: 0.7327 - val_loss: 0.4645 - val_acc: 0.8199
Epoch 8/10
acc: 0.7304 - val_loss: 0.4645 - val_acc: 0.8232
Epoch 9/10
acc: 0.7366 - val_loss: 0.4779 - val_acc: 0.8199
Epoch 10/10
acc: 0.7463 - val_loss: 0.4769 - val_acc: 0.8135
```



316/316 [=========== ] - 17s 55ms/step

Test loss: 0.5168347962294952

Test accuracy: 75.32% \_\_\_\_\_ clarinet TRAIN precision recall f1-score False 0.80 0.87 0.83 1357 True 0.37 0.26 0.31 401 accuracy 0.73 1758 macro avg 0.57 0.59 0.57 1758 weighted avg 0.70 0.73 0.71 1758 **TEST** precision recall f1-score support False 0.80 0.86 0.83 240 True 0.43 0.34 0.38 76 0.73 316 accuracy macro avg 0.62 0.60 0.61 316 weighted avg 0.72 0.72 0.73 316 Train on 1292 samples, validate on 229 samples Epoch 1/10 acc: 0.5457 - val\_loss: 0.5255 - val\_acc: 0.7511 Epoch 2/10 acc: 0.6354 - val\_loss: 0.5193 - val\_acc: 0.7642 Epoch 3/10 acc: 0.6889 - val\_loss: 0.4405 - val\_acc: 0.8253 Epoch 4/10 acc: 0.7252 - val\_loss: 0.6367 - val\_acc: 0.6594 Epoch 5/10 acc: 0.7384 - val\_loss: 0.4469 - val\_acc: 0.8166 Epoch 6/10 acc: 0.7291 - val\_loss: 0.4300 - val\_acc: 0.8515 

acc: 0.7740 - val\_loss: 0.4340 - val\_acc: 0.8253

acc: 0.7678 - val\_loss: 0.4227 - val\_acc: 0.8428

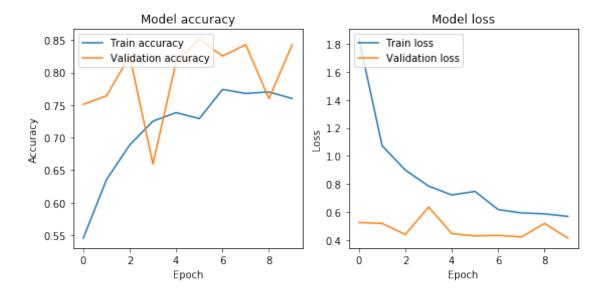
Epoch 8/10

Epoch 9/10

acc: 0.7701 - val\_loss: 0.5193 - val\_acc: 0.7598

Epoch 10/10

acc: 0.7601 - val\_loss: 0.4148 - val\_acc: 0.8428



214/214 [======== ] - 13s 59ms/step

Test loss: 0.3548090073549859

Test accuracy: 84.11%

-----

cymbals

TRAIN

	precision	recall	f1-score	support
False	0.94	0.65	0.77	468
True	0.83	0.98	0.90	824
			0.00	4000
accuracy			0.86	1292
macro avg	0.88	0.81	0.83	1292
weighted avg	0.87	0.86	0.85	1292
TEST				
ILDI	precision	recall	f1-score	support
False	0.88	0.59	0.71	74
True	0.82	0.96	0.88	140
accuracy			0.83	214

```
0.84
weighted avg
             0.83
                  0.82
                       214
Train on 1284 samples, validate on 236 samples
Epoch 1/10
acc: 0.5717 - val_loss: 0.6638 - val_acc: 0.6525
Epoch 2/10
acc: 0.6706 - val_loss: 0.5718 - val_acc: 0.7458
Epoch 3/10
acc: 0.7103 - val_loss: 0.6901 - val_acc: 0.7203
Epoch 4/10
acc: 0.7173 - val_loss: 0.4587 - val_acc: 0.8178
Epoch 5/10
acc: 0.7305 - val_loss: 0.4888 - val_acc: 0.7881
Epoch 6/10
acc: 0.7204 - val_loss: 0.4940 - val_acc: 0.8051
Epoch 7/10
acc: 0.7656 - val_loss: 0.4645 - val_acc: 0.8136
Epoch 8/10
acc: 0.7773 - val_loss: 0.4360 - val_acc: 0.8475
acc: 0.7578 - val_loss: 0.5090 - val_acc: 0.7966
Epoch 10/10
acc: 0.8022 - val_loss: 0.4521 - val_acc: 0.8305
```

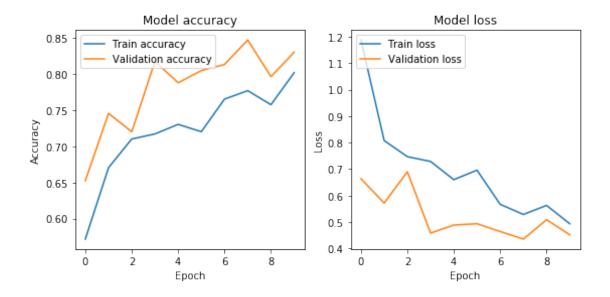
0.80

214

0.85

macro avg

0.78



227/227 [========= ] - 13s 57ms/step

Test loss: 0.5031188363414504

Test accuracy: 82.38%

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drums

TRAIN

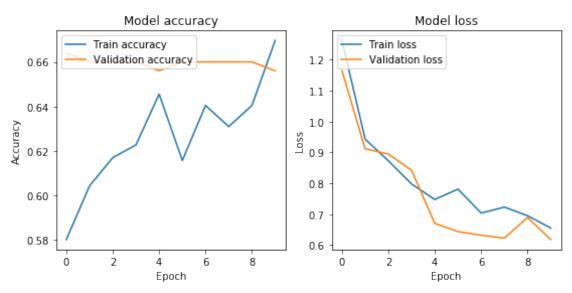
	precision	recall	f1-score	support
False	0.90	0.72	0.80	466
True	0.86	0.95	0.90	818
accuracy			0.87	1284
macro avg	0.88	0.84	0.85	1284
weighted avg	0.87	0.87	0.87	1284
TEST	precision	recall	f1-score	support
False	0.91	0.67	0.77	91
True	0.81	0.96	0.88	136
accuracy			0.84	227
macro avg	0.86	0.81	0.83	227
weighted avg	0.85	0.84	0.84	227

Train on 1577 samples, validate on 250 samples

Epoch 1/10

acc: 0.5802 - val\_loss: 1.1643 - val\_acc: 0.6640

```
Epoch 2/10
1577/1577 [============= ] - 251s 159ms/step - loss: 0.9430 -
acc: 0.6043 - val_loss: 0.9120 - val_acc: 0.6600
Epoch 3/10
acc: 0.6170 - val_loss: 0.8948 - val_acc: 0.6600
Epoch 4/10
acc: 0.6227 - val_loss: 0.8425 - val_acc: 0.6600
Epoch 5/10
acc: 0.6455 - val_loss: 0.6705 - val_acc: 0.6560
Epoch 6/10
acc: 0.6157 - val_loss: 0.6440 - val_acc: 0.6600
Epoch 7/10
acc: 0.6405 - val_loss: 0.6321 - val_acc: 0.6600
Epoch 8/10
acc: 0.6309 - val_loss: 0.6230 - val_acc: 0.6600
Epoch 9/10
acc: 0.6405 - val_loss: 0.6895 - val_acc: 0.6600
Epoch 10/10
acc: 0.6696 - val_loss: 0.6181 - val_acc: 0.6560
```



257/257 [========= ] - 15s 56ms/step

Test loss: 0.6230789652594333

Test accuracy: 66.15%

f]	lute

Ilute				
TRAIN				
	precision	recall	f1-score	support
	-			
False	0.73	0.84	0.78	1094
True	0.44	0.30	0.36	483
accuracy			0.67	1577
macro avg	0.59	0.57	0.57	1577
weighted avg	0.64	0.67	0.65	1577
TEST				
	precision	recall	f1-score	support
	_			
False	0.71	0.80	0.76	177
True	0.40	0.29	0.33	80
accuracy			0.64	257
macro avg	0.56	0.54	0.54	257
_				
weighted avg	0.61	0.64	0.62	257

Train on 1275 samples, validate on 177 samples

Epoch 1/10

acc: 0.5757 - val\_loss: 0.7326 - val\_acc: 0.4802

acc: 0.5906 - val\_loss: 0.7925 - val\_acc: 0.6497

acc: 0.6141 - val\_loss: 0.6851 - val\_acc: 0.6497

Epoch 4/10

acc: 0.6659 - val loss: 0.6389 - val acc: 0.6554

Epoch 5/10

acc: 0.6471 - val\_loss: 0.6019 - val\_acc: 0.6667

Epoch 6/10

acc: 0.6635 - val\_loss: 0.6976 - val\_acc: 0.6497

Epoch 7/10

acc: 0.6518 - val\_loss: 0.6054 - val\_acc: 0.6667

Epoch 8/10

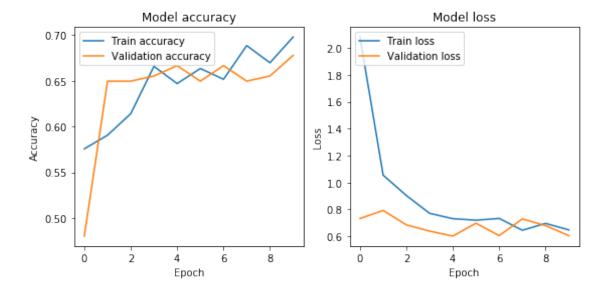
acc: 0.6886 - val\_loss: 0.7294 - val\_acc: 0.6497

Epoch 9/10

acc: 0.6698 - val\_loss: 0.6796 - val\_acc: 0.6554

Epoch 10/10

acc: 0.6980 - val\_loss: 0.6050 - val\_acc: 0.6780



198/198 [========= ] - 13s 65ms/step

Test loss: 0.5209842715600524

Test accuracy: 73.74%

TRAIN

-----

guitar

precision recall f1-score support 0.03 False 1.00 0.06 387 0.70 1.00 True 0.83 888 0.71 1275 accuracy 0.44 macro avg 0.85 0.52 1275 weighted avg 0.79 0.71 0.59 1275

TEST precision recall f1-score support

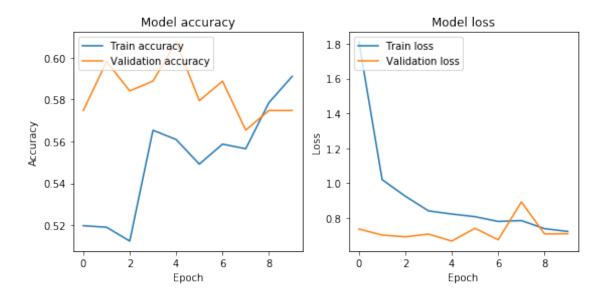
False 1.00 0.05 0.09 63

True 0.69 1.00 0.82 135

```
0.85 0.52
                     0.45
 macro avg
                           198
weighted avg
          0.79
               0.70
                     0.59
                           198
Train on 1362 samples, validate on 214 samples
Epoch 1/10
acc: 0.5198 - val_loss: 0.7355 - val_acc: 0.5748
Epoch 2/10
acc: 0.5191 - val_loss: 0.7009 - val_acc: 0.5981
1362/1362 [============= ] - 234s 172ms/step - loss: 0.9239 -
acc: 0.5125 - val_loss: 0.6909 - val_acc: 0.5841
1362/1362 [============== ] - 235s 173ms/step - loss: 0.8397 -
acc: 0.5653 - val_loss: 0.7065 - val_acc: 0.5888
Epoch 5/10
acc: 0.5609 - val_loss: 0.6664 - val_acc: 0.6075
Epoch 6/10
acc: 0.5492 - val_loss: 0.7398 - val_acc: 0.5794
Epoch 7/10
acc: 0.5587 - val_loss: 0.6739 - val_acc: 0.5888
Epoch 8/10
acc: 0.5565 - val_loss: 0.8913 - val_acc: 0.5654
Epoch 9/10
acc: 0.5786 - val_loss: 0.7077 - val_acc: 0.5748
Epoch 10/10
acc: 0.5910 - val loss: 0.7086 - val acc: 0.5748
```

0.70

accuracy



226/226 [========== ] - 15s 65ms/step

Test loss: 0.6503403548118287

Test accuracy: 63.72%

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 ${\tt mallet\_percussion}$ 

TRATN

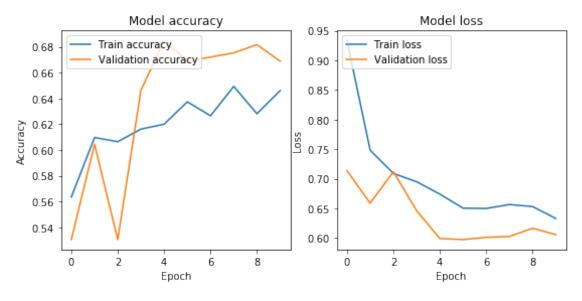
IRAIN					
	precision	recall	f1-score	support	
False	0.66	0.79	0.72	810	
raise	0.00	0.79	0.72	010	
True	0.57	0.41	0.48	552	
accuracy			0.64	1362	
macro avg	0.62	0.60	0.60	1362	
weighted avg	0.63	0.64	0.62	1362	
worghood avg	0.00	0.01	0.02	1002	
TEST					
	precision	recall	f1-score	support	
False	0.65	0.75	0.70	137	
True	0.50	0.38	0.43	89	
accuracy			0.61	226	
macro avg	0 50	0 E7	0.57	226	
macro avg	0.58	0.57	0.57	220	

Train on 1842 samples, validate on 311 samples

Epoch 1/10

acc: 0.5635 - val\_loss: 0.7137 - val\_acc: 0.5305

```
Epoch 2/10
acc: 0.6097 - val_loss: 0.6588 - val_acc: 0.6045
Epoch 3/10
1842/1842 [============= ] - 321s 174ms/step - loss: 0.7091 -
acc: 0.6064 - val_loss: 0.7119 - val_acc: 0.5305
Epoch 4/10
acc: 0.6162 - val_loss: 0.6463 - val_acc: 0.6463
Epoch 5/10
acc: 0.6200 - val_loss: 0.5991 - val_acc: 0.6849
Epoch 6/10
acc: 0.6374 - val_loss: 0.5973 - val_acc: 0.6688
Epoch 7/10
1842/1842 [============= ] - 316s 172ms/step - loss: 0.6499 -
acc: 0.6265 - val_loss: 0.6011 - val_acc: 0.6720
Epoch 8/10
1842/1842 [============== ] - 318s 173ms/step - loss: 0.6565 -
acc: 0.6493 - val_loss: 0.6026 - val_acc: 0.6752
Epoch 9/10
acc: 0.6281 - val_loss: 0.6164 - val_acc: 0.6817
Epoch 10/10
acc: 0.6460 - val_loss: 0.6057 - val_acc: 0.6688
```



311/311 [=========== ] - 19s 61ms/step

Test loss: 0.6496247246717717

Test accuracy: 60.13%

\_\_\_\_\_

### mandolin

TRAIN

	precision	recall	f1-score	support
False	0.78	0.65	0.71	1216
True	0.48	0.63	0.55	626
accuracy			0.65	1842
macro avg	0.63	0.64	0.63	1842
weighted avg	0.68	0.65	0.65	1842
TEST				
	precision	recall	f1-score	support
False	0.67	0.62	0.65	192
True	0.46	ο Ε4		
	0.46	0.51	0.48	119
accuracy	0.46	0.51	0.48	311
accuracy macro avg	0.46	0.51		

Train on 1416 samples, validate on 224 samples

Epoch 1/10

acc: 0.6010 - val\_loss: 0.7526 - val\_acc: 0.6473

Epoch 2/10

acc: 0.6010 - val\_loss: 0.6324 - val\_acc: 0.6339

Epoch 3/10

acc: 0.6243 - val\_loss: 0.6312 - val\_acc: 0.6473

Epoch 4/10

acc: 0.6236 - val\_loss: 0.6213 - val\_acc: 0.6295

Epoch 5/10

acc: 0.6250 - val\_loss: 0.6040 - val\_acc: 0.6250

Epoch 6/10

acc: 0.6292 - val\_loss: 0.5942 - val\_acc: 0.6518

Epoch 7/10

acc: 0.6504 - val\_loss: 0.6264 - val\_acc: 0.6250

Epoch 8/10

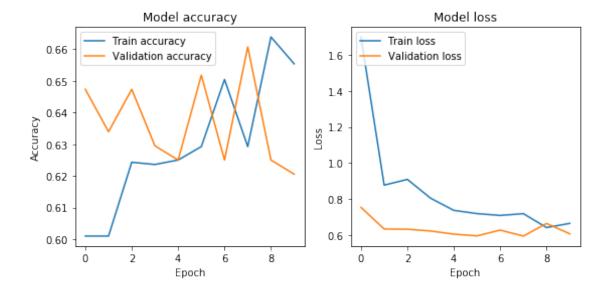
acc: 0.6292 - val\_loss: 0.5931 - val\_acc: 0.6607

Epoch 9/10

acc: 0.6638 - val\_loss: 0.6633 - val\_acc: 0.6250

Epoch 10/10

acc: 0.6554 - val\_loss: 0.6056 - val\_acc: 0.6205



250/250 [========== ] - 16s 63ms/step

Test loss: 0.5691616973876953

Test accuracy: 70.40%

-----

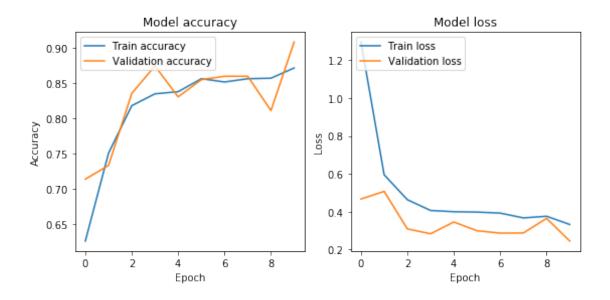
organ

TRAIN precision recall f1-score support 0.44 False 0.92 0.60 968 0.43 0.92 True 0.59 448 0.59 1416 accuracy macro avg 0.68 0.68 0.59 1416 weighted avg 0.77 0.59 0.59 1416 TEST precision recall f1-score support False 0.96 0.42 0.59 173 True 0.43 0.96 0.59 77

```
0.69 0.69
                  0.59
 macro avg
                       250
weighted avg
        0.80
            0.59
                  0.59
                       250
Train on 1310 samples, validate on 206 samples
Epoch 1/10
acc: 0.6260 - val_loss: 0.4672 - val_acc: 0.7136
Epoch 2/10
acc: 0.7504 - val_loss: 0.5076 - val_acc: 0.7330
acc: 0.8176 - val_loss: 0.3095 - val_acc: 0.8350
acc: 0.8344 - val_loss: 0.2838 - val_acc: 0.8738
acc: 0.8374 - val_loss: 0.3460 - val_acc: 0.8301
Epoch 6/10
acc: 0.8557 - val_loss: 0.2999 - val_acc: 0.8544
Epoch 7/10
acc: 0.8511 - val_loss: 0.2873 - val_acc: 0.8592
Epoch 8/10
acc: 0.8557 - val_loss: 0.2881 - val_acc: 0.8592
Epoch 9/10
acc: 0.8565 - val_loss: 0.3651 - val_acc: 0.8107
Epoch 10/10
acc: 0.8710 - val loss: 0.2453 - val acc: 0.9078
```

0.59

accuracy



204/204 [======== ] - 14s 71ms/step

Test loss: 0.26010071734587353

Test accuracy: 90.20%

-----

piano

TRAIN

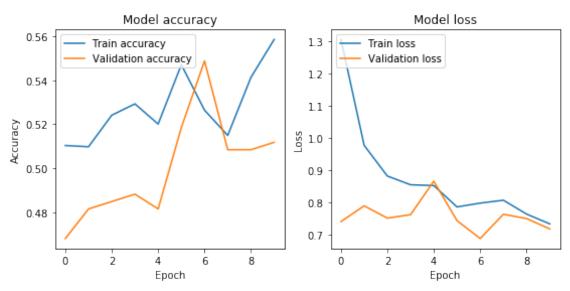
ITAIN				
	precision	recall	f1-score	support
False	0.95	0.67	0.78	419
True	0.86	0.98	0.92	891
0.000000.000			Λ 00	1210
accuracy			0.88	1310
macro avg	0.90	0.83	0.85	1310
weighted avg	0.89	0.88	0.88	1310
TEST				
	precision	recall	f1-score	support
False	0.92	0.67	0.77	66
True	0.86	0.97	0.91	138
accuracy			0.87	204
macro avg	0.89	0.82	0.84	204
weighted avg	0.88	0.87	0.87	204

Train on 1742 samples, validate on 297 samples

Epoch 1/10

acc: 0.5103 - val\_loss: 0.7396 - val\_acc: 0.4680

```
Epoch 2/10
acc: 0.5098 - val_loss: 0.7886 - val_acc: 0.4815
Epoch 3/10
acc: 0.5241 - val_loss: 0.7504 - val_acc: 0.4848
Epoch 4/10
acc: 0.5293 - val_loss: 0.7612 - val_acc: 0.4882
Epoch 5/10
acc: 0.5201 - val_loss: 0.8653 - val_acc: 0.4815
Epoch 6/10
acc: 0.5471 - val_loss: 0.7427 - val_acc: 0.5185
Epoch 7/10
1742/1742 [============= ] - 279s 160ms/step - loss: 0.7971 -
acc: 0.5264 - val_loss: 0.6869 - val_acc: 0.5488
Epoch 8/10
acc: 0.5149 - val_loss: 0.7625 - val_acc: 0.5084
Epoch 9/10
acc: 0.5413 - val_loss: 0.7490 - val_acc: 0.5084
Epoch 10/10
acc: 0.5586 - val_loss: 0.7169 - val_acc: 0.5118
```



326/326 [=========== ] - 20s 63ms/step

Test loss: 0.6907476643843153

Test accuracy	: 55.83%					
saxophone TRAIN						
	precision	recall	f1-score	support		
	0.65					
True	0.52	0.79	0.63	828		
accuracy			0.56	1742		
macro avg	0.58	0.57	0.54	1742		
weighted avg	0.59	0.56	0.54	1742		
TEST						
	precision	recall	f1-score	support		
False	0.64	0.40	0.49	174		
	0.52					
accuracy			0.56	326		
•	0.58	0.57				
weighted avg						
Train on 1212	samples, va	lidate on	187 sampl	es		
Epoch 1/10						
1212/1212 [===			:=====] -	193s 159ms/	step - loss	: 1.1954 -
acc: 0.5883 -					•	
Epoch 2/10			-		_	
1212/1212 [===					step - loss	: 0.9718 -
acc: 0.5817 - Epoch 3/10	Val_loss: U	.7849 - ₹	al_acc: 0.	0/38		
1212/1212 [===			=====1 _	100a 150ma/	stan - loss	. 0 8206 -
acc: 0.6229 -					scep 1055	. 0.0230
Epoch 4/10	Vai_1055. 0	.0010 v	ar_acc. o.	0751		
1212/1212 [===			=====1 -	197s 163ms/	step - loss	. 0.7158 -
acc: 0.6617 -					200p 1000	. 0.11200
Epoch 5/10						
1212/1212 [===			=====] -	192s 159ms/	step - loss	: 0.6693 -
acc: 0.6782 -					•	
Epoch 6/10						
1212/1212 [===		======	======] -	193s 160ms/	step - loss	: 0.6676 -
acc: 0.6733 -						
Epoch 7/10						
1212/1212 [===		=======	:=====] - -	195s 161ms/	step - loss	: 0.6492 -

acc: 0.6873 - val\_loss: 0.5100 - val\_acc: 0.7433

Epoch 8/10

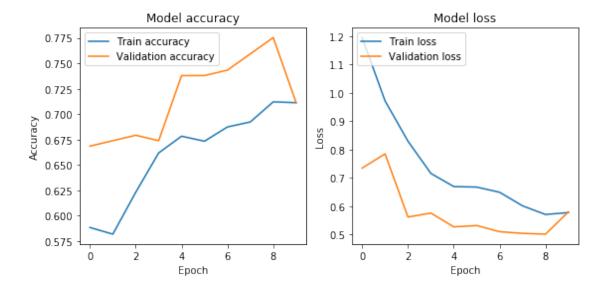
acc: 0.6922 - val\_loss: 0.5042 - val\_acc: 0.7594

Epoch 9/10

acc: 0.7120 - val\_loss: 0.5013 - val\_acc: 0.7754

Epoch 10/10

acc: 0.7112 - val\_loss: 0.5801 - val\_acc: 0.7112



203/203 [========== ] - 12s 58ms/step

Test loss: 0.5563669988674483

Test accuracy: 70.94%

-----

synthesizer

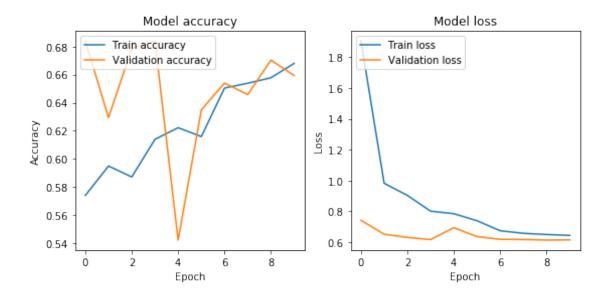
TRAIN

	precision	recall	f1-score	support
False	0.68	0.73	0.71	386
True	0.87	0.84	0.85	826
accuracy			0.81	1212
macro avg	0.78	0.79	0.78	1212
weighted avg	0.81	0.81	0.81	1212
TEST				
	precision	recall	f1-score	support
False	0.61	0.67	0.64	64
True	0.84	0.81	0.82	139

```
0.73 0.74
                          0.73
 macro avg
                                  203
weighted avg
            0.77
                  0.76
                          0.77
                                 203
Train on 2054 samples, validate on 367 samples
Epoch 1/10
acc: 0.5740 - val_loss: 0.7412 - val_acc: 0.6839
Epoch 2/10
2054/2054 [============== ] - 330s 161ms/step - loss: 0.9819 -
acc: 0.5949 - val_loss: 0.6515 - val_acc: 0.6294
2054/2054 [============= ] - 333s 162ms/step - loss: 0.9033 -
acc: 0.5871 - val_loss: 0.6305 - val_acc: 0.6785
2054/2054 [============= ] - 331s 161ms/step - loss: 0.8008 -
acc: 0.6139 - val_loss: 0.6165 - val_acc: 0.6839
2054/2054 [============== ] - 330s 161ms/step - loss: 0.7845 -
acc: 0.6222 - val_loss: 0.6934 - val_acc: 0.5422
Epoch 6/10
acc: 0.6159 - val_loss: 0.6362 - val_acc: 0.6349
Epoch 7/10
2054/2054 [============== ] - 329s 160ms/step - loss: 0.6739 -
acc: 0.6504 - val_loss: 0.6179 - val_acc: 0.6540
Epoch 8/10
acc: 0.6538 - val_loss: 0.6172 - val_acc: 0.6458
Epoch 9/10
acc: 0.6577 - val_loss: 0.6133 - val_acc: 0.6703
Epoch 10/10
acc: 0.6680 - val loss: 0.6146 - val acc: 0.6594
```

0.76

accuracy



339/339 [========== ] - 23s 66ms/step

Test loss: 0.6200752998523655

Test accuracy: 66.96%

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#### trombone

TRAIN

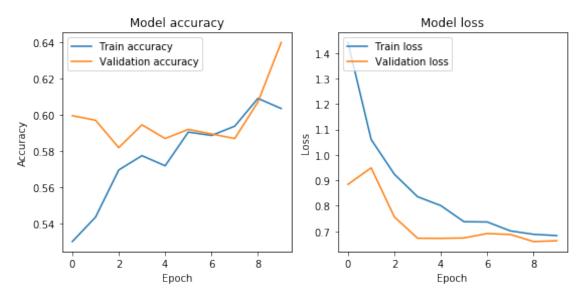
	precision	recall	f1-score	support
False	0.81	0.60	0.69	1415
True	0.44	0.68	0.53	639
accuracy			0.63	2054
macro avg	0.62	0.64	0.61	2054
weighted avg	0.69	0.63	0.64	2054
TEST				
	precision	recall	f1-score	support
	•			
False	0.72	0.54	0.62	227
True	0.38	0.58	0.46	112
accuracy			0.55	339
macro avg	0.55	0.56	0.54	339
weighted avg				

Train on 2156 samples, validate on 397 samples

Epoch 1/10

acc: 0.5301 - val\_loss: 0.8843 - val\_acc: 0.5995

```
Epoch 2/10
2156/2156 [============== ] - 423s 196ms/step - loss: 1.0604 -
acc: 0.5436 - val_loss: 0.9492 - val_acc: 0.5970
Epoch 3/10
2156/2156 [============== ] - 451s 209ms/step - loss: 0.9239 -
acc: 0.5696 - val_loss: 0.7565 - val_acc: 0.5819
Epoch 4/10
acc: 0.5775 - val_loss: 0.6728 - val_acc: 0.5945
Epoch 5/10
acc: 0.5719 - val_loss: 0.6723 - val_acc: 0.5869
Epoch 6/10
acc: 0.5904 - val_loss: 0.6739 - val_acc: 0.5919
Epoch 7/10
2156/2156 [============= ] - 363s 168ms/step - loss: 0.7367 -
acc: 0.5886 - val_loss: 0.6913 - val_acc: 0.5894
Epoch 8/10
2156/2156 [============== ] - 367s 170ms/step - loss: 0.7015 -
acc: 0.5937 - val_loss: 0.6875 - val_acc: 0.5869
Epoch 9/10
acc: 0.6090 - val_loss: 0.6597 - val_acc: 0.6071
Epoch 10/10
2156/2156 [============== ] - 382s 177ms/step - loss: 0.6832 -
acc: 0.6034 - val_loss: 0.6629 - val_acc: 0.6398
```



363/363 [============ ] - 23s 63ms/step

Test loss: 0.698793343604432

#### Test accuracy: 54.82% trumpet TRAIN precision recall f1-score support False 0.86 0.27 0.41 1324 True 0.44 0.93 0.60 832 0.52 2156 accuracy 0.65 0.60 0.50 macro avg 2156 0.70 weighted avg 0.52 0.48 2156 TEST precision recall f1-score support 0.65 False 0.19 0.30 208 True 0.44 0.86 0.58 155 accuracy 0.48 363 0.44 macro avg 0.54 0.53 363 weighted avg 0.56 0.48 0.42 363 Train on 1827 samples, validate on 314 samples Epoch 1/10 acc: 0.5862 - val\_loss: 0.7261 - val\_acc: 0.4745 acc: 0.6169 - val\_loss: 0.7184 - val\_acc: 0.4713 acc: 0.6147 - val\_loss: 0.6660 - val\_acc: 0.5732 Epoch 4/10 acc: 0.6388 - val loss: 0.7648 - val acc: 0.4140 Epoch 5/10 acc: 0.6366 - val\_loss: 0.7076 - val\_acc: 0.5096 Epoch 6/10 acc: 0.6475 - val\_loss: 0.5712 - val\_acc: 0.7006 Epoch 7/10

1827/1827 [============= ] - 324s 177ms/step - loss: 0.6534 -

acc: 0.6508 - val\_loss: 0.5850 - val\_acc: 0.6943

Epoch 8/10

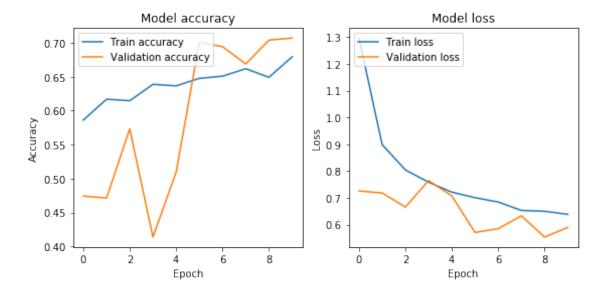
acc: 0.6617 - val\_loss: 0.6333 - val\_acc: 0.6688

Epoch 9/10

acc: 0.6492 - val\_loss: 0.5539 - val\_acc: 0.7038

Epoch 10/10

acc: 0.6793 - val\_loss: 0.5899 - val\_acc: 0.7070



284/284 [=========== ] - 18s 64ms/step

Test loss: 0.6137258754649633

Test accuracy: 65.85%

TRAIN

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precision recall f1-score support 0.86 0.33 False 0.48 1260 0.37 0.88 True 0.52 567 0.50 1827 accuracy macro avg 0.61 0.60 0.50 1827 weighted avg 0.71 0.50 0.49 1827

TEST precision recall f1-score support

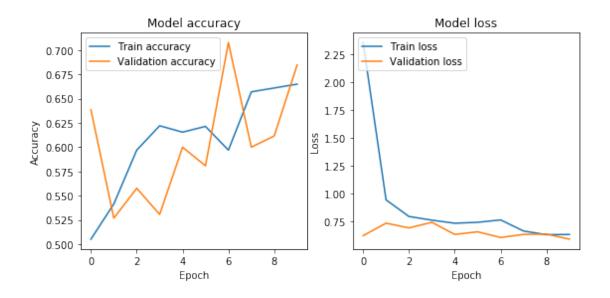
False 0.87 0.35 0.50 204

True 0.34 0.86 0.49 80

```
0.61 0.61
                  0.50
 macro avg
                       284
weighted avg
        0.72
            0.50
                  0.50
                       284
Train on 1516 samples, validate on 260 samples
Epoch 1/10
acc: 0.5053 - val_loss: 0.6211 - val_acc: 0.6385
Epoch 2/10
acc: 0.5416 - val_loss: 0.7335 - val_acc: 0.5269
acc: 0.5970 - val_loss: 0.6909 - val_acc: 0.5577
acc: 0.6220 - val_loss: 0.7413 - val_acc: 0.5308
Epoch 5/10
acc: 0.6154 - val_loss: 0.6322 - val_acc: 0.6000
Epoch 6/10
acc: 0.6214 - val_loss: 0.6556 - val_acc: 0.5808
Epoch 7/10
acc: 0.5970 - val_loss: 0.6045 - val_acc: 0.7077
Epoch 8/10
acc: 0.6570 - val_loss: 0.6324 - val_acc: 0.6000
Epoch 9/10
acc: 0.6609 - val_loss: 0.6350 - val_acc: 0.6115
Epoch 10/10
acc: 0.6649 - val loss: 0.5894 - val acc: 0.6846
```

0.50

accuracy



257/257 [========= ] - 17s 66ms/step

Test loss: 0.548202626436137

Test accuracy: 72.37%

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violin

TRAIN

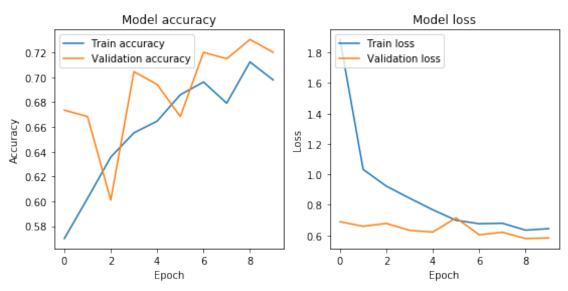
	precision	recall	f1-score	support
False	0.92	0.46	0.61	640
True	0.71	0.97	0.82	876
accuracy			0.76	1516
macro avg	0.82	0.72	0.72	1516
weighted avg	0.80	0.76	0.73	1516
TEST				
ILDI	precision	recall	f1-score	support
False	0.93	0.39	0.55	106
True	0.69	0.98	0.81	151
accuracy			0.74	257
macro avg	0.81	0.68	0.68	257
weighted avg	0.79	0.74	0.70	257

Train on 1172 samples, validate on 193 samples

Epoch 1/10

acc: 0.5700 - val\_loss: 0.6892 - val\_acc: 0.6736

```
Epoch 2/10
acc: 0.6024 - val_loss: 0.6594 - val_acc: 0.6684
Epoch 3/10
acc: 0.6357 - val_loss: 0.6784 - val_acc: 0.6010
Epoch 4/10
acc: 0.6553 - val_loss: 0.6328 - val_acc: 0.7047
Epoch 5/10
acc: 0.6647 - val_loss: 0.6213 - val_acc: 0.6943
Epoch 6/10
acc: 0.6860 - val_loss: 0.7145 - val_acc: 0.6684
Epoch 7/10
acc: 0.6962 - val_loss: 0.6035 - val_acc: 0.7202
Epoch 8/10
acc: 0.6792 - val_loss: 0.6201 - val_acc: 0.7150
Epoch 9/10
acc: 0.7125 - val_loss: 0.5788 - val_acc: 0.7306
Epoch 10/10
acc: 0.6980 - val_loss: 0.5828 - val_acc: 0.7202
```



199/199 [=========] - 14s 69ms/step

Test loss: 0.5129846924513428

Test accuracy: 77.89%

weighted avg

voice				
TRAIN	Ī			
	precision	recall	f1-score	support
False	0.91	0.40	0.55	437
True	0.73	0.98	0.84	735
accuracy			0.76	1172
macro avg	0.82	0.69	0.70	1172
weighted avg	0.80	0.76	0.73	1172
TEST				
	precision	recall	f1-score	support
False	0.86	0.37	0.52	65
True	0.76	0.97	0.85	134
accuracy			0.77	199
macro avg	0.81	0.67	0.68	199

0.79

0.77

```
[8]: import matplotlib.pyplot as plt
   from pylab import plot, show, figure, imshow, xlim, ylim, title
   def plot_history():
       plt.figure(figsize=(9,4))
       plt.subplot(1,2,1)
       plt.plot(history.history['acc'])
       plt.plot(history.history['val_acc'])
       plt.title('Model accuracy')
       plt.ylabel('Accuracy')
       plt.xlabel('Epoch')
       plt.legend(['Train accuracy', 'Validation accuracy'], loc='upper left')
       plt.subplot(1,2,2)
       plt.plot(history.history['loss'])
       plt.plot(history.history['val_loss'])
       plt.title('Model loss')
       plt.ylabel('Loss')
       plt.xlabel('Epoch')
       plt.legend(['Train loss', 'Validation loss'], loc='upper left')
       plt.show()
```

0.74

```
# Step 3: simplify the data by averaging over time
# Instead of having time-varying features, we'll summarize each track by

→ its mean feature vector over time

    X_train_inst_sklearn = np.mean(X_train_inst, axis=1)

    X_test_inst_sklearn = np.mean(X_test_inst, axis=1)

    X_train_inst_sklearn = X_train_inst_sklearn.astype('float32')

    X_train_inst_sklearn = lb.util.normalize(X_train_inst_sklearn)

"""

np.savez('models.npz',model=)
```