classifier_analysis

August 7, 2025

[ ]:
```
%pip install numpy pandas plotly scikit-learn tqdm umap-learn torch tensorflow␣
↪keras transformers matplotlib scikit-learn
```

1 Muiscal Instruments classification, and topic related data analysis

This notebook consists of Analyzing the dataset of Musical Instruments photos. First the images are embedded using the generic model (microsoft ResNet). Then fine-tuned EfficientNet model is used. The notebook uses dataset from kaggle (https://www.kaggle.com/datasets/gpiosenka/musical-instruments-image-classification).

[1]:
```
from pathlib import Path
from typing import Any, Literal, List, Union
from tqdm.notebook import tqdm
import os

from transformers import AutoModel

import torch

import numpy as np
from numpy.typing import NDArray
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.metrics import accuracy_score, ConfusionMatrixDisplay,␣
↪confusion_matrix, adjusted_rand_score
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import KMeans, AgglomerativeClustering

from umap import UMAP

import tensorflow as tf
import keras
from keras import layers
```

```
import plotly.io as pio
import plotly.express as px
import plotly.graph_objects as go
from scipy.spatial import ConvexHull

from PIL import Image
from IPython import display

import kagglehub

import random

from transformers import AutoFeatureExtractor, AutoModel
```

[2]:
```
try:
  import google.colab
  IN_COLAB = True
except:
  IN_COLAB = False

import warnings
warnings.filterwarnings("ignore")
```

2 Dataset download and preperation

[5]:
```
path = kagglehub.dataset_download("gpiosenka/
 ↪musical-instruments-image-classification")
BASE_DIR = path
if IN_COLAB:
    pio.renderers.default = "colab"
else:
    pio.renderers.default = "vscode"
```

```
Warning: Looks like you're using an outdated `kagglehub` version (installed:
0.3.11), please consider upgrading to the latest version (0.3.12).
```

[6]:
```
instrument_idxs = {}
idx_instruments = {}

with open('instruments.csv', 'r') as f:
    for line in f:
        idx, instrument = line.strip().split(',')
        instrument_idxs[instrument] = int(idx)
        idx_instruments[int(idx)] = instrument
```

[7]:
```
image_paths_train = []
image_paths_test = []
image_paths_validate = []
labels_train = []
labels_test = []
labels_validate = []

file_list = os.listdir(os.path.join(BASE_DIR, "train"))

for instrument in file_list:
    idx = instrument_idxs[instrument]
    for img in os.listdir(os.path.join(BASE_DIR, "train", instrument)):
        image_paths_train.append(os.path.join(BASE_DIR, "train", instrument,␣
↪img))
        labels_train.append(idx)
    for img in os.listdir(os.path.join(BASE_DIR, "test", instrument)):
        image_paths_test.append(os.path.join(BASE_DIR, "test", instrument, img))
        labels_test.append(idx)
    for img in os.listdir(os.path.join(BASE_DIR, "valid", instrument)):
        image_paths_validate.append(os.path.join(BASE_DIR, "valid", instrument,␣
↪img))
        labels_validate.append(idx)


image_paths_train = np.array(image_paths_train)
image_paths_test = np.array(image_paths_test)
image_paths_validate = np.array(image_paths_validate)
labels_train = np.array(labels_train)
labels_test = np.array(labels_test)
labels_validate = np.array(labels_validate)
```

3 Useful functions

First, we will declare some fuctions that will be helpful later

[8]:
```
def project_vectors(data: NDArray, technique: str = "tsne", **options):
    if technique == "pca":
        transformer = PCA(**options)
    elif technique == "tsne":
        transformer = TSNE(**options)
    elif technique == "umap":
        transformer = UMAP(**options)
    else:
        raise ValueError(
            f"Invalid technique: {technique}. Choose from 'pca', 'tsne', or␣
↪'umap'."
        )
```

```python
    transformed_data = transformer.fit_transform(data)
    return transformed_data
```

[9]:
```python
def cluster_df(df, embeddings, clusters_num = 30) -> None:
    kmeans = KMeans(n_clusters=clusters_num, random_state=0)
    kmeans_labels = kmeans.fit_predict(embeddings)

    AC = AgglomerativeClustering(n_clusters=clusters_num)
    AC_labels = AC.fit_predict(embeddings)

    ari_kmeans = adjusted_rand_score(labels_validate, kmeans_labels)
    ari_AC = adjusted_rand_score(labels_validate, AC_labels)

    df['KMeans Cluster'] = kmeans_labels.astype(str)
    df['AC Cluster'] = AC_labels.astype(str)

    print(f'KMeans ari: {ari_kmeans}')
    print(f'AC ari: {ari_AC}')

def show_clusters(df, title, method: Literal["KMeans", "AC"] = 'KMeans'):

    if method not in ['KMeans', 'AC']:
        raise ValueError("Use either KMeans or AC as method")

    fig_kmeans = px.scatter(
        df,
        x='x',
        y='y',
        color='instrument',
        title=title
    )

    # Add convex hulls
    for cluster in df[f'{method} Cluster'].unique():
        cluster_points = df[df[f'{method} Cluster'] == cluster][['x', 'y']].
 ↪values
        if len(cluster_points) < 3:
            # ConvexHull requires at least 3 points
            continue
        hull = ConvexHull(cluster_points)
        hull_pts = cluster_points[hull.vertices]
        hull_pts = np.append(hull_pts, [hull_pts[0]], axis=0)  # Close the loop

        fig_kmeans.add_trace(go.Scatter(
            x=hull_pts[:, 0],
            y=hull_pts[:, 1],
```

```
            mode='lines',
            line=dict(color='rgba(0,0,0,0.3)', width=2),
            fill='toself',
            fillcolor='rgba(0,0,0,0.1)',
            hoverinfo='skip',
            showlegend=False
        ))

    fig_kmeans.show()
```

4 Image Embeddings using Microsoft ResNet-50 model

[10]:
```
def generate_image_embeddings(image_path: str | Path, model_name: str =␣
 ↪"microsoft/resnet-50"):
    image = Image.open(image_path)

    #Some photos are grey scaled. Feture extractor expects 3 channel image
    if image.mode != 'RGB':
        image = image.convert('RGB')

    feature_extractor = AutoFeatureExtractor.from_pretrained(model_name)
    model = AutoModel.from_pretrained(model_name)

    inputs = feature_extractor(images=image, return_tensors="pt")


    with torch.no_grad():
        outputs = model(**inputs)

    if hasattr(outputs, 'pooler_output'):
        embeddings = outputs.pooler_output.numpy()
    else:
        embeddings = outputs.last_hidden_state.mean(dim=1).numpy()

    return embeddings.squeeze()
```

[11]:
```
image_embeddings = []
for img in tqdm(image_paths_validate):
    embeddings = generate_image_embeddings(img)
    image_embeddings.append(embeddings)
```

```
0%|          | 0/150 [00:00<?, ?it/s]
```

[12]:
```
scaler = MinMaxScaler()
norm_image_embeddings = scaler.fit_transform(image_embeddings)
reduced_image_embeddings = project_vectors(np.array(norm_image_embeddings),␣
 ↪technique="umap", n_components=2, random_state=42)
```

```
reduced_image_embeddings_pca = project_vectors(np.array(norm_image_embeddings),␣
    ↪technique="pca", n_components=2, random_state=42)
```

[13]:
```
df_embeddings = pd.DataFrame(reduced_image_embeddings, columns=["x", "y"])
df_embeddings["instrument"] = [idx_instruments[i] for i in labels_validate]

df_embeddings_pca = pd.DataFrame(reduced_image_embeddings_pca, columns=["x",␣
    ↪"y"])
df_embeddings_pca["instrument"] = [idx_instruments[i] for i in labels_validate]
```

[14]:
```
cluster_df(df_embeddings, reduced_image_embeddings)
```

```
KMeans ari: 0.6429622943597348
AC ari: 0.6566892848838438
```

[15]:
```
show_clusters(df_embeddings, 'KMeans Clustering of ResNet embeddings with␣
    ↪UMAP', 'KMeans')
```

5 Observations

1. There are two class-pairs that were connected into one clusters:

   - bongo drums and drums
   - clavichord and piano

   Both of theese pairs consist of intstruments that are similar-looking.

2. ARI is equal to 0.65, which is pretty good score, for high amount of classes (30), and non-specific model

[16]:
```
cluster_df(df_embeddings_pca, reduced_image_embeddings_pca)
```

```
KMeans ari: 0.25423193322026005
AC ari: 0.27014835958698946
```

[17]:
```
show_clusters(df_embeddings_pca, 'Agglomerative Clustering of ResNet embeddings␣
    ↪with PCA', 'AC')
```

6 Observations

Despite having much lower ACI, PCA preserves global structures and allows us to get more insight. - Instruments that are simillar are often put next to each others: - Guitar, Banjo, Dulcimer - Drums, Bongo drums - Trumpet, Trombone, Tuba

7 Using dedicated pre-trained model

7.1 Model accuracy analysis

[18]:
```
def load_and_preprocess_image(image_path: Union[str, Path], target_size=(224,␣
↪224)) -> np.ndarray:
    image = tf.io.read_file(image_path)
    image = tf.image.decode_jpeg(image, channels=3)
    image = tf.image.resize(image, target_size)  # Resize as needed
    image_array = np.array(image)
    return image_array

def generate_image_embeddings_with_keras(
        image_paths: List[Union[str, Path]],
        keras_model_path: str = "model.keras",
        batch_size: int = 1,
        target_size=(224, 224)
) -> np.ndarray:

    model = tf.keras.models.load_model(keras_model_path)
    all_embeddings = []

    for i in tqdm(range(0, len(image_paths), batch_size)):
        batch_paths = image_paths[i:i + batch_size]
        batch_images = [load_and_preprocess_image(path, target_size) for path␣
↪in batch_paths]
        batch_tensor = np.stack(batch_images, axis=0)

        embeddings = model.predict(batch_tensor, verbose=0)
        all_embeddings.append(embeddings)

    return np.vstack(all_embeddings).squeeze()

image_embeddings = generate_image_embeddings_with_keras(image_paths_validate,␣
↪keras_model_path="model.keras", batch_size=16)
```

```
  0%|          | 0/10 [00:00<?, ?it/s]
```

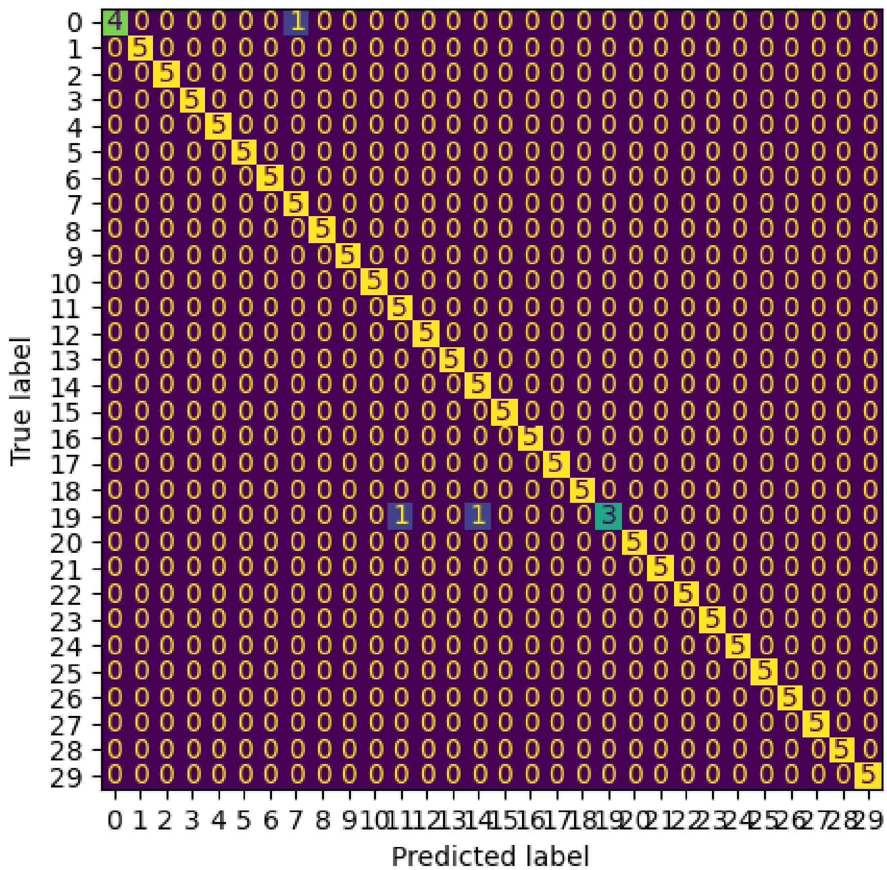
[19]:
```
print(f'Accuracy score: {accuracy_score(labels_validate, np.
↪argmax(image_embeddings, axis=1))}')
```

```
Accuracy score: 0.98
```

[20]:
```
_, count = np.unique(labels_validate, return_counts=True)
cm1 = ConfusionMatrixDisplay(confusion_matrix(labels_validate, np.
↪argmax(image_embeddings, axis=1)))

cm1.plot(colorbar=False)
```

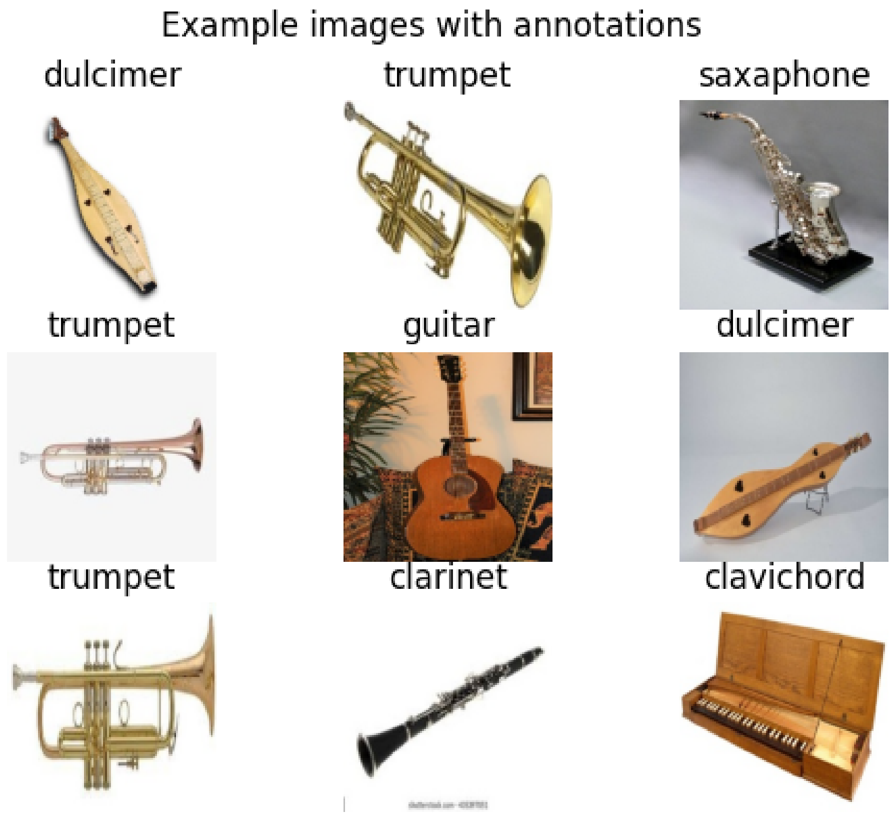
```
plt.tight_layout()
plt.show()
```



[125]:
```
full_dataset = list(zip(image_paths_validate, labels_validate))
random.seed(42)
random.shuffle(full_dataset)
```

[126]:
```
fig, ax = plt.subplots(3, 3)

for i in range(9):
    img, idx = full_dataset[i]
    ax = plt.subplot(3, 3, i + 1)
    image = Image.open(img)
    plt.imshow(np.array(image).astype("int16"))
    plt.title(idx_instruments[idx])
    plt.axis("off")
plt.suptitle("Example images with annotations")
plt.show()
```



7.2 Example of image prediction

[127]:
```
def softmax(values):
    exp_values = np.exp(values)
    exp_values_sum = np.sum(exp_values)
    return exp_values/exp_values_sum

def classify_photo_with_dl(img_path: str):
    logits = generate_image_embeddings_with_keras([img_path],␣
 ↪keras_model_path="model.keras", batch_size=1)
    probs = softmax(logits)
    probs = [f'{round(100 * x)}%' for x in probs]
    return pd.DataFrame(probs, index=instrument_idxs.keys(),␣
 ↪columns=['probability']).sort_values('probability', ascending = False).head()

def show_classification(df, img_path):
    img = Image.open(img_path)
    img = img.resize((224, 224))
    display.display(df)
    display.display(img)
```

[128]:
```
show_classification(classify_photo_with_dl("guitar.jpg"), 'guitar.jpg')
```

```
  0%|          | 0/1 [00:00<?, ?it/s]
```

	probability
guitar	85%
sitar	8%
banjo	2%
violin	1%
piano	0%

8 Embeddings generated as nn clasifier output

[21]:
```
scaler = MinMaxScaler()
norm_embeddings = scaler.fit_transform(image_embeddings)
```

[22]:
```
reduced_embeddings_PCA = project_vectors(np.array(norm_embeddings),␣
 ↪technique="pca", n_components=2, random_state=42)
reduced_embeddings_umap = project_vectors(np.array(norm_embeddings),␣
 ↪technique="umap", n_components=2, random_state=42)
```

[24]:
```
df_NNembedings_umap = pd.DataFrame(reduced_embeddings_umap, columns=["x", "y"])
df_NNembedings_umap["instrument"] = [idx_instruments[i] for i in␣
 ↪labels_validate]

df_NNembedings_PCA = pd.DataFrame(reduced_embeddings_PCA, columns=["x", "y"])
df_NNembedings_PCA["instrument"] = [idx_instruments[i] for i in labels_validate]
```

[25]:
```
cluster_df(df_NNembedings_umap, reduced_embeddings_umap)
```

```
KMeans ari: 0.938909389093891
AC ari: 0.9441167445190767
```

[26]:
```
show_clusters(df_NNembedings_umap, f'Agglomerative Clustering with UMAP', 'AC')
```

[27]:
```
cluster_df(df_NNembedings_PCA, reduced_embeddings_PCA)
```

```
KMeans ari: 0.38845298617845564
AC ari: 0.44985170389201623
```

[28]:
```
show_clusters(df_NNembedings_PCA, "Agglomerative Clustering with PCA")
```

9 Observations:

1. Clustering done on UMAP projections provides almost ideal ARI (0.94)
2. For both ResNet and Fine Tuned model projecting embeddings with PCA makes it harder to cluster, achieving much lower ARI

10 Fine tuning EfficientNet model

[16]:
```
data_augmentation = keras.Sequential([
    layers.RandomFlip("horizontal"),
    layers.RandomBrightness(0.1),
    layers.RandomContrast(0.1)
])
```

[17]:
```
image_size = (224, 224)
batch_size = 128

def load_image(path, label):
    image = tf.io.read_file(path)
    image = tf.image.decode_jpeg(image, channels=3)
    image = tf.image.resize(image, image_size)  # Resize as needed
    image = data_augmentation(image)
    return image, label
```

[18]:
```
X_train, X_val, y_train, y_val = image_paths_train, image_paths_test,␣
 ↪labels_train, labels_test

train_ds = tf.data.Dataset.from_tensor_slices((X_train, y_train))
train_ds = train_ds.shuffle(buffer_size=1000, reshuffle_each_iteration=True)
train_ds = train_ds.map(load_image, num_parallel_calls=tf.data.AUTOTUNE)
train_ds = train_ds.batch(batch_size).prefetch(tf.data.AUTOTUNE)

test_ds = tf.data.Dataset.from_tensor_slices((X_val, y_val))
```

```
test_ds = test_ds.map(load_image, num_parallel_calls=tf.data.AUTOTUNE)
test_ds = test_ds.batch(batch_size).prefetch(tf.data.AUTOTUNE)
```

[19]:
```
plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(np.array(images[i]).astype("int16"))
        plt.title(instrument_idxs[labels[i].numpy()])
        plt.axis("off")
```

[ ]:
```python
base_model = keras.applications.EfficientNetB0(
    input_shape=image_size + (3,),
    include_top=False,
    weights="imagenet"
)
base_model.trainable = True

inputs = keras.Input(shape=image_size + (3,))
x = keras.applications.efficientnet.preprocess_input(inputs)
x = base_model(x)
x = layers.GlobalAveragePooling2D()(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(20, activation=None)(x)
model = keras.Model(inputs, outputs)

model.compile(
    optimizer=keras.optimizers.Adam(1e-5),
    loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True,␣
 ↪reduction="sum_over_batch_size"),
    metrics=[keras.metrics.SparseCategoricalAccuracy()],
)

#Save each model to choose the best one
callbacks = [
    keras.callbacks.ModelCheckpoint("save_at_{epoch}.keras"),
]
```

[ ]:
```python
history = model.fit(
    train_ds,
    epochs=100,
    validation_data=test_ds,
    callbacks=callbacks
)
```