Sport Image Classification and Object Detection Using Computer Vision Techniques

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Introduction

Computer vision (CV) uses a combination of traditional artificial intelligence (AI), machine learning (ML), and image processing to understand images. Techniques such as feature detection and extraction, image processing, and object recognition are essential to the implementation of CV. The techniques presented can be applied to perform image classification and object detection for various applications. For this analysis, a dataset comprised of sport images collected from Google Images using Images Scrapper is used (Konapure, 2020). The dataset consists of 22 folders with the label name as the corresponding sport category which include badminton, baseball, basketball, boxing, chess, cricket, fencing, football, formula 1, gymnastics, hockey, ice hockey, kabaddi, motocross, shooting, swimming, table tennis, tennis, volleyball, weightlifting, wrestling, and WWE. Each folder consists of around 800-900 images with a total of 14184 images in the dataset.

Object detection is important in sports as it allows for player and equipment tracking. This allows for analysis of how individual players move throughout the game and detects patterns in their behavior. From this, optimal player positions can be determined, and areas of growth can be identified. CV allows for a model to be developed that is able to classify images by the sport depicted and apply transfer learning for object detection in the images. AI principles such as neural networks, deep learning, and other machine learning techniques are implemented to successfully complete image classification and object detection on the selected dataset.

Pre-Processing

The initial step of standard image processing is to pre-process the raw images from the dataset with the goal of shape transformation, data quality, and model quality to prepare them to be used for the model training. The code used for this is included in Appendix A. The input images into the model are first transformed into a consistent size of 224x224 pixels with 3 channels corresponding to the color images.

Next, the images are checked for data quality to ensure that no pixels are masked or assigned a value of -inf. To assist in the model training process, pixel values are rescaled to lie in a range from [0-1] as the learning optimizers function the best with small data values (Lakshmanan, et al., 2021). A random sample of the pre-processed images from the dataset are shown in Figure 1. After completing the image pre-processing, the dataset is split into training and validation sets with 11348 images used for training and 2836 used for validation. The validation set is further split into a validation dataset and a test dataset used for the final model evaluation.

Figure 1

Sample of pre-processed images from the dataset

Classification

The code used for the image classification model is included in Appendix B. ResNet-50 uses convolutional neural networks (CNNs) as a base for the pretrained deep learning model for image classification. The model is pretrained using the ImageNet database which contains over 14 million images corresponding to 1000 categories and is considered a benchmark for image classification tasks (About ImageNet, 2019). The ResNet-50 model used for this analysis has a deep architecture with 50 layers and over 23 million parameters and is pre-trained using the ImageNet dataset for 5 epochs. The training set generated from the sport dataset is used to fit the model with a categorical cross-entropy loss and the Adam optimizer. The model structure is summarized in Figure 2.

Figure 2

ResNet-50 model structure

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 224, 224, 3)       0

 feature_extraction_layer (  (None, 2048)              23564800
 KerasLayer)

 dense (Dense)               (None, 128)               262272

 output_layer (Dense)        (None, 22)                2838

=================================================================
Total params: 23829910 (90.90 MB)
Trainable params: 265110 (1.01 MB)
Non-trainable params: 23564800 (89.89 MB)
_________________________________________________________________
```

The training and validation loss and accuracy are compared in the learning curves in Figure 3. It can be seen on the lefthand side of the figure that the training loss decreases smoothly indicating that the batch size and optimizer setting have been decently chosen; however, the validation loss does not

decrease at all indicating that there may be overfitting occurring. Regularization is one technique that can be implemented to mitigate the effects of overfitting. The model accuracy on the training and validation set are shown on the righthand side of Figure 3. The accuracy on the training dataset continues increasing as training continues, while the accuracy on the validation dataset plateaus. The lines from this graph are smooth as well, providing the same insights as those from the loss graph. The accuracy obtained on the test dataset is 83% which is better than the 4.5% that is expected from random choice. This indicates that the model is able to learn and is decent at classifying images. An example of the model predicting image categories is shown in Figure 4. The model is able to correctly predict 8 out of the 9 images presented.

Figure 3

ResNet-50 learning curves

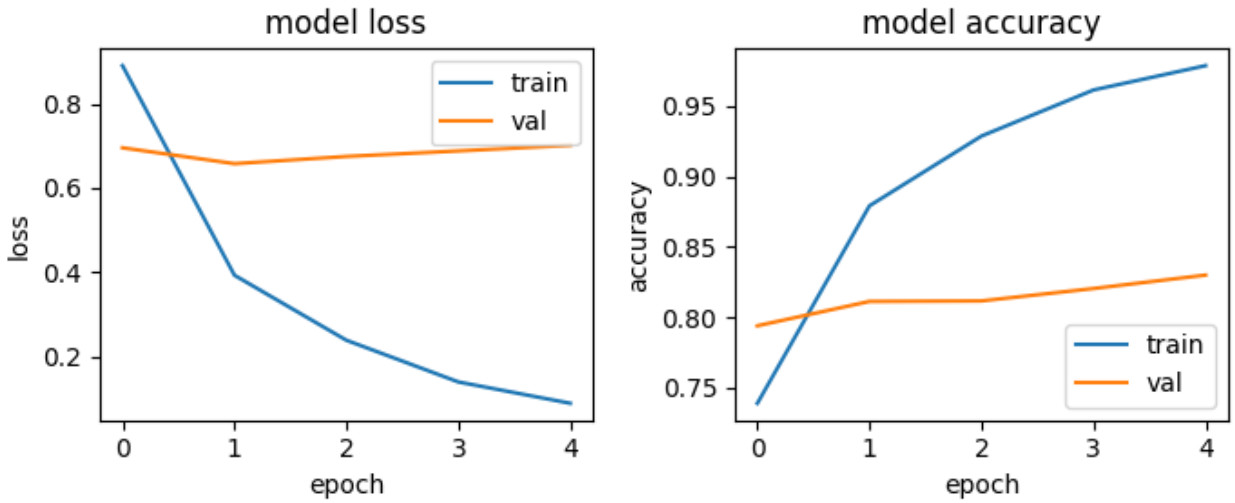
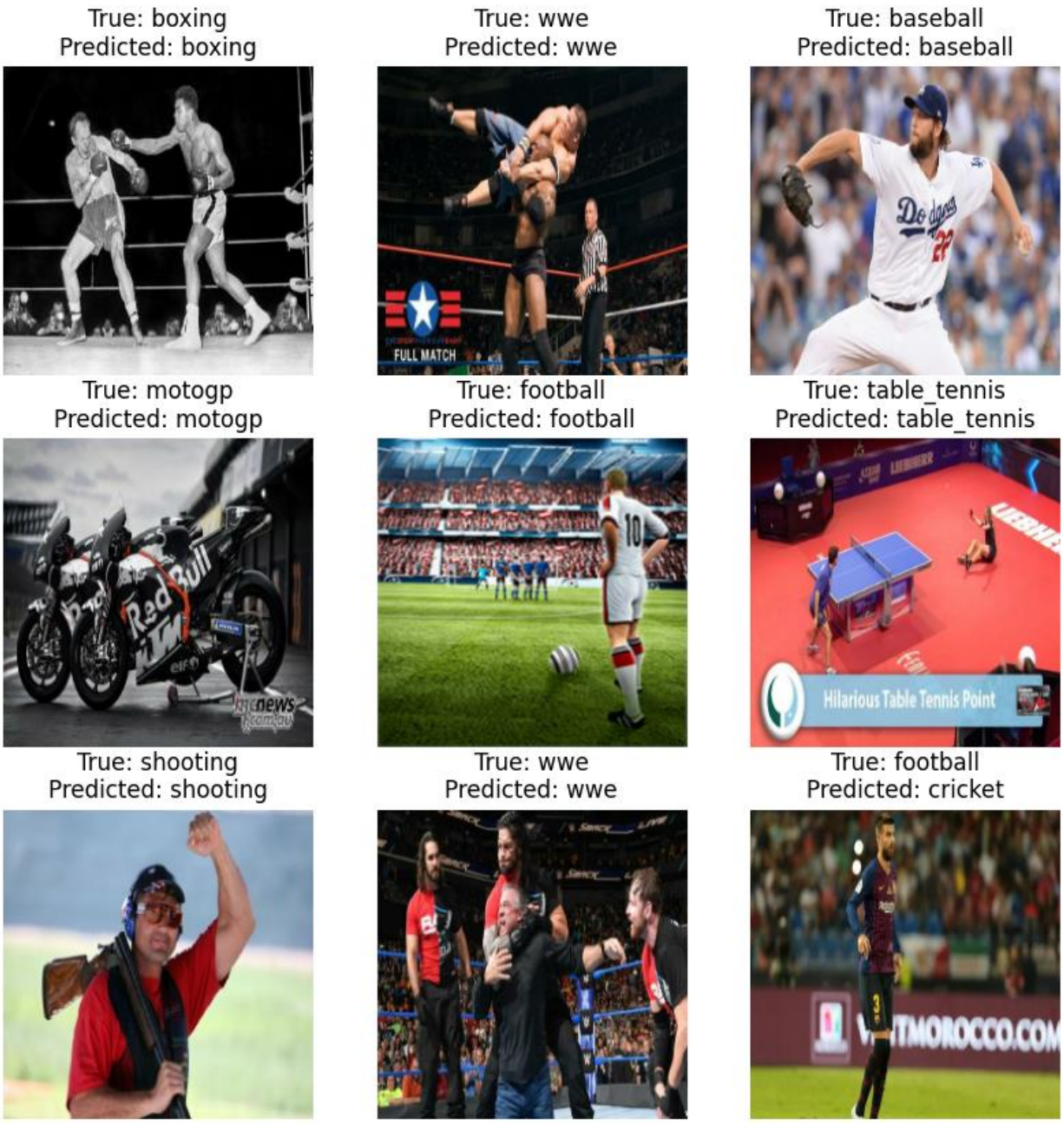


Figure 4

ResNet-50 prediction



Object Detection

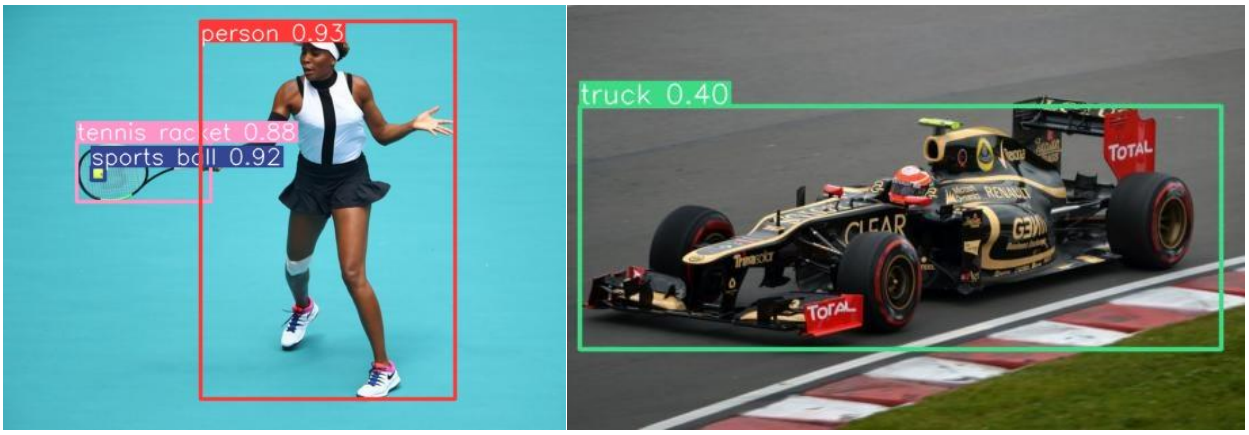
In contrast to image classification, object detection provides the location and class of an object in the image by generating a bounding box around the object and providing the confidence level for the class. For this analysis, the results generated from the YOLOv8 and RetinaNet are compared. The code used for object detection is included in Appendix C.

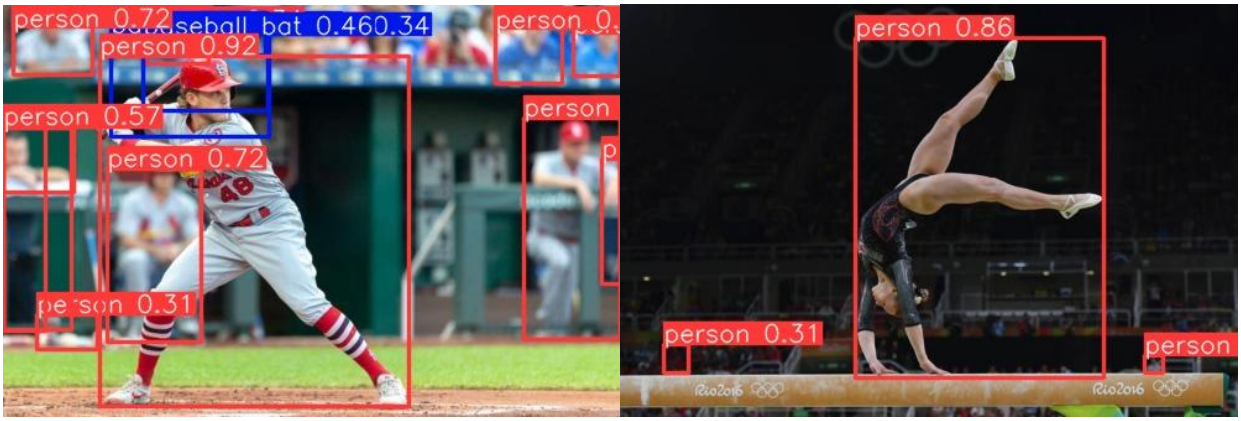
YOLOv8

YOLOv8 is the latest version of the You Only Look Once object detection and image segmentation model and is pretrained using the Common Objects in Context (COCO) dataset. This dataset is a large-scale object detection, segmentation, and captioning dataset designed for research in a wide variety of object categories and is considered a benchmark for computer vision models. The dataset consists of 80 object categories including people, cars, animals, and sport equipment (Jocher & Laughing, 2023). The YOLOv8 model used is YOLOv8n with 3.2 million parameters and pre-trained using the COCO dataset for 10 epochs (Jocher et al., 2023). The model is used to predict the location and class of objects in four random images from the sport dataset. The results are shown in Figure 5.

Figure 5

Results from YOLOv8



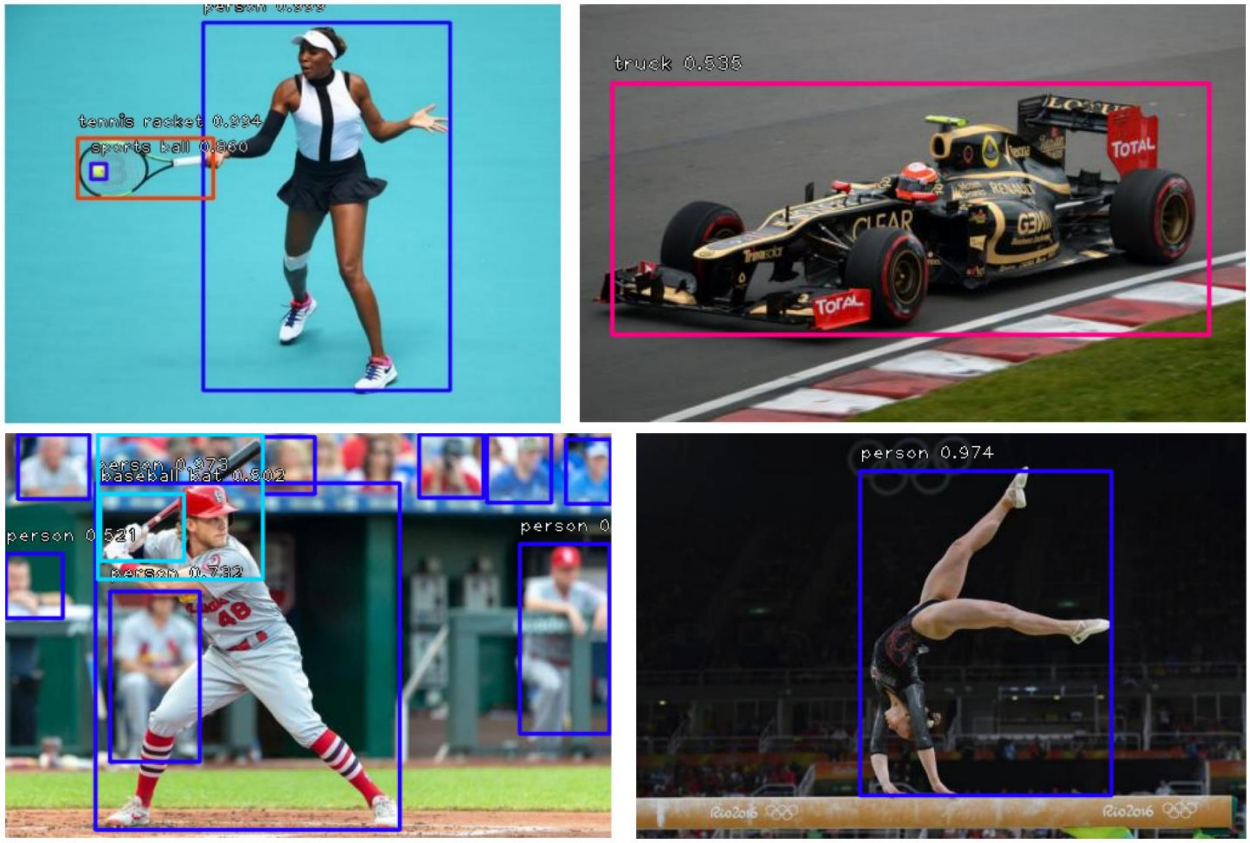


RetinaNet

The RetinaNet architecture differs from the YOLO architecture in three major ways. It includes feature pyramid networks (FPNs) to detect objects at multiple scales, anchor boxes to make training easier, and a focal loss function to balance the foreground and background. The additional layers that form the FPN allow for proper spatial and semantic information at all scales. The FPN computes feature maps which are used with the anchor boxes as inputs for the model detection. Nine anchor boxes are used in the RetinaNet model with three different aspect ratios and three unique sizes. To ensure that training with the model can be completed, the focal loss is introduced to assign small values on empty backgrounds (Lakshmanan et al., 2021). Similar to the YOLOv8 model, the RetinaNet is pre-trained on the COCO dataset. The results produced by the RetinaNet model on the same images as the YOLOv8 are shown in Figure 6.

Figure 6

Results from RetinaNet



YOLOv8 and RetinaNet Comparison

From Figure 2 and Figure 3 it can be seen that the YOLOv8 and the RetinaNet models produce similar results. The RetinaNet model has a higher confidence level when classifying people and sport equipment. Additionally, the model is able to better differentiate between the foreground and background as shown in the bottom two images in the figures. No bounding boxes are used in gymnastics image for the people in the background whereas the YOLOv8 model identifies two people in the background with a low confidence level.

Both models incorrectly label the formula 1 car as a truck; however, the YOLOv8 model has a lower confidence level. This mislabel can be attributed to the generic categories from the COCO dataset used to train the model. For more precise results, a custom dataset with object annotations related to sports can be used to pre-train the models.

Conclusion

When training the ResNet-50 model on the sport dataset for image classification, the model achieves an accuracy of 83%. Both the YOLOv8 and the RetinaNet models produce high confidence levels when recognizing people and sport equipment in the images. These models prove to be important in sports as they form the foundation for player and equipment tracking. The results from the object detection models can be extended to video clips of matches and an analysis of how individual players perform throughout the game can be completed. Recommendations for player development can then be made from this analysis.

References

About ImageNet. (2015, May 19). ImageNet. Retrieved December 9, 2023, from https://www.image-net.org/about.php

Jocher, G. & Laughing, Q. (2023, November 22). *COCO Dataset*. Ultralytics. Retrieved December 4, 2023, from https://docs.ultralytics.com/datasets/detect/coco/

Jocher, G., Laughing, Q. & Exel, A. (2023, November 22). *Object Detection*. Ultralytics. Retrieved December 4, 2023, from https://docs.ultralytics.com/tasks/detect/

Konapure, R. (2020). *Sports Image Dataset* [Data set]. Kaggle. https://www.kaggle.com/datasets/rishikeshkonapure/sports-image-dataset/data

Lakshmanan, V., Gorner, M., & Gillard, R. (2021). *Practical machine learning for computer vision: End-to-end machine learning for images.* O'Reilly.

Appendix A

Some outputs have been suppressed for clarity

Pre-processing

[1]:
```
!pip install -q kaggle
!pip install -q patool
```

```
                                     93.7/93.7 kB
1.1 MB/s eta 0:00:00
```

[2]:
```
# Not all imports are used but thought it was important to show all the different
# approaches tried and experimented with.
import numpy as np
import matplotlib.pyplot as plt
import cv2
import os
import requests
from PIL import Image
from io import BytesIO
import random
import pickle
from sklearn.model_selection import train_test_split
import patoolib

# Data visualization
import seaborn as sns
import numpy as np
import pandas as pd
import tensorflow as tf
import tensorflow_hub as hub


# Keras
from keras.models import Sequential
from tensorflow.keras import layers
from keras.layers import Dense, Dropout, Flatten, Resizing
from keras.optimizers import SGD, Adam, Adadelta, RMSprop
```

```
import keras.backend as K
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Scaling data
from sklearn.preprocessing import StandardScaler
# Classification Report
from sklearn.metrics import classification_report
from keras.utils import to_categorical
from sklearn.metrics import confusion_matrix
from google.colab import files
from google.colab.patches import cv2_imshow
```

[ ]:
```
## THIS WILL TRIGGER A UPLOAD BUTTON LOOKING FOR THE KAGGLE KEY
# upload kaggle.json that was generated from kaggle when getting api key
files.upload()

# creates and unzips dataset on google drive /content folder
! mkdir ~/.kaggle
! cp kaggle.json ~/.kaggle/
! chmod 600 ~/.kaggle/kaggle.json
! kaggle datasets download -d rishikeshkonapure/sports-image-dataset/
! mkdir kaggle_data
! unzip /content/sports-image-dataset.zip -d kaggle_data
```

Appendix B

Some outputs have been suppressed for clarity

Building Classification with Resnet50_v2_50 model

Resnet does get rescaled 1/255

efficientNet does not require image rescale - if we had time this is another model we could look into

[ ]: ResNet50 works best with input images of 224 x 224

```
IMAGE_SIZE = (224, 224)
BATCH_SIZE = 32
data_dir = "/content/kaggle_data/data"

train_ds, val_ds = tf.keras.utils.image_dataset_from_directory(data_dir,
 ↪labels="inferred",
 ↪image_size=IMAGE_SIZE,
 ↪validation_split=0.2,
 ↪"categorical",
                                                                label_mode=
                                                                subset="both",
```

```
    batch_size=BATCH_SIZE,
    color_mode="grayscale"
    seed=58)

categories = train_ds.class_names
# Viewing the shape and object of the

def inspect_dataset(dataset, name="train"):
  print("Dataset:", name)
  for image_batch, labels_batch in dataset:
    print("image batch size", image_batch.shape)
    print("label batch shape ", labels_batch.shape)
    print("label batch", labels_batch[0])
    print("\n ")
    break

inspect_dataset(train_ds, "TRAIN")
inspect_dataset(val_ds, "VALIDATION")
```

```
Found 14184 files belonging to 22 classes.
Using 11348 files for training.
Using 2836 files for validation.
Dataset: TRAIN
image batch size (32, 224, 224, 3)
label batch shape  (32, 22)
label batch tf.Tensor([0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0. 0. 0.], shape=(22,), dtype=float32)


Dataset: VALIDATION
image batch size (32, 224, 224, 3)
label batch shape  (32, 22)
label batch tf.Tensor([0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0. 1. 0.], shape=(22,), dtype=float32)
```

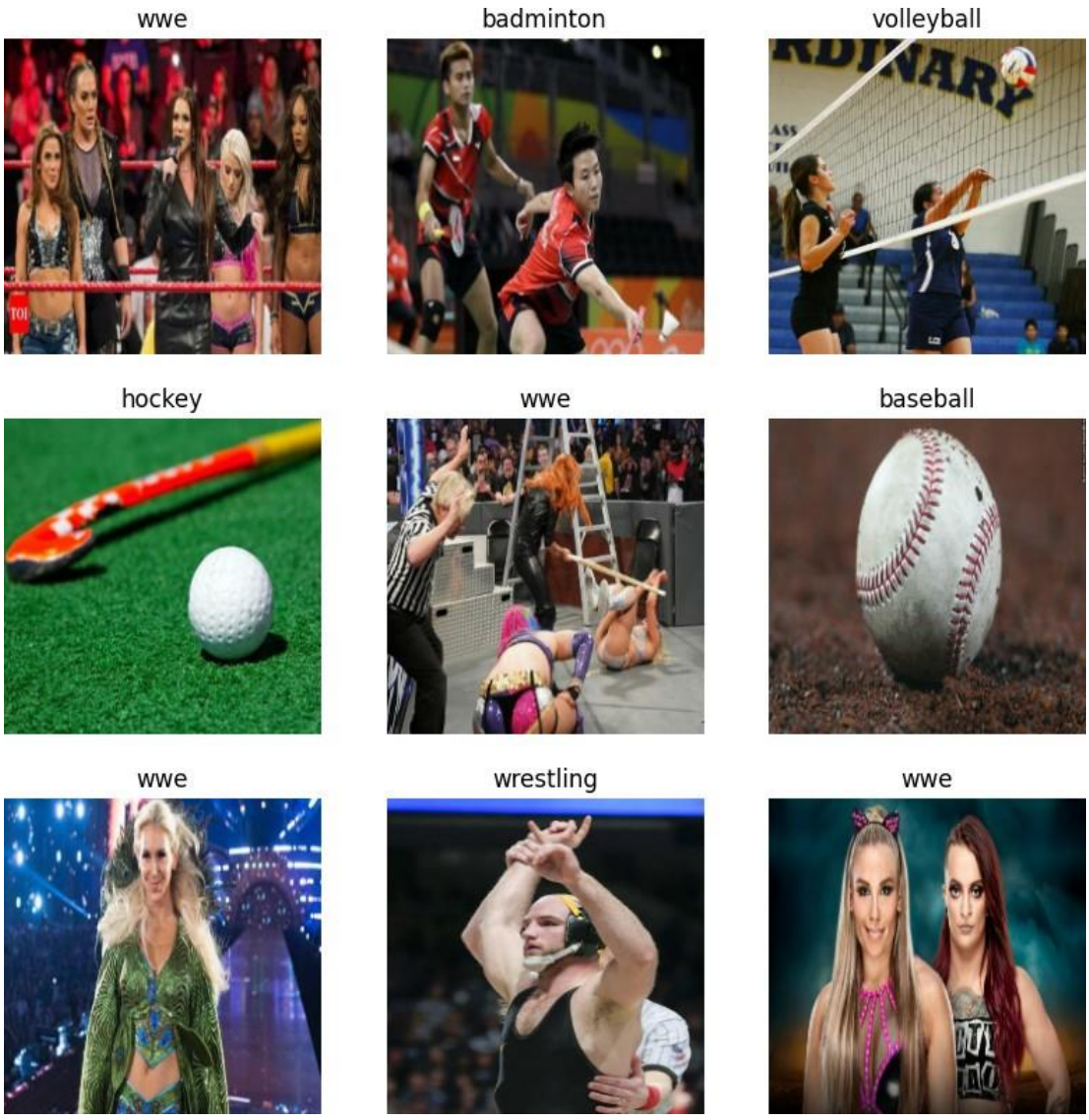
[ ]:
```
# Creating spliting  test / validation  datasets
test_val_ds = val_ds.take(int(0.7 * len(val_ds)))
val_ds = val_ds.skip(int(0.7 * len(val_ds)))
inspect_dataset(test_val_ds, "TEST")
inspect_dataset(val_ds, "NEW VALIDATION")
```

```
AUTOTUNE = tf.data.AUTOTUNE

#    train_ds    =    train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
# val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

```
Dataset: TEST
image batch size (32, 224, 224, 3)
label batch shape  (32, 22)
label batch tf.Tensor([0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0. 1. 0.], shape=(22,), dtype=float32)
```

```
Dataset: New validation
image batch size (32, 224, 224, 3)
label batch shape  (32, 22)
label batch tf.Tensor([0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0. 0. 0.], shape=(22,), dtype=float32)
```

[ ]:
```
def display_img(train_ds):
  class_names = train_ds.class_names
  plt.figure(figsize=(10, 10))
  for images, labels in train_ds.take(2):
    for i in range(9):
      ax = plt.subplot(3, 3, i + 1)
      image_np = np.array(images[i], dtype=np.float32) / 255.0 # converting to
↪numpy and scaling values
      plt.imshow(image_np)    # Needed to use a converted image
      label_index = tf.argmax(labels[i]).numpy()
      plt.title(class_names[label_index])
      plt.axis("off")

display_img(train_ds)
```



[ ]:
```
# Resnet 50 V2 feature vector
resnet_url = "https://tfhub.dev/google/imagenet/resnet_v2_50/feature_vector/4"

# Original: EfficientNetB0 feature vector (version 1)
efficientnet_url = "https://tfhub.dev/tensorflow/efficientnet/b0/feature-vector/
↪1"

def create_model(model_url, num_classes=len(categories)):
  """
  Takes a TensorFlow Hub URL and creates a Keras Sequential model with it.

  Args:
```

```
    model_url (str): A TensorFlow Hub feature extraction URL.
    num_classes (int): Number of output neurons in output layer,
      should be equal to number of target classes, default 10.

  Returns:
    An uncompiled Keras Sequential model with model_url as feature
    extractor layer and Dense output layer with num_classes outputs.
  """

  rescaling_layer = layers.Rescaling(1./255, input_shape=(IMAGE_SIZE[0],␣
↪IMAGE_SIZE[1], 3))

  # Download the pretrained model and save it as a Keras layer
  feature_extractor_layer = hub.KerasLayer(model_url,
                                           trainable=False, # freeze the␣
↪underlying patterns
                                           name='feature_extraction_layer',
                                           input_shape=(224,224,3)) # define␣
↪the input image shape

  # Create our own model
  model = tf.keras.Sequential([
    rescaling_layer,
    feature_extractor_layer, # use the feature extraction layer as the
    Dense(128, activation='relu'),
    Dense(num_classes, activation='softmax', name='output_layer') # create our␣
↪own output layer
  ])

  return model
```

Note: each Keras Application expects a specific kind of input preprocessing. For ResNet, call tf.keras.applications.resnet.preprocess_input on your inputs before passing them to the model. resnet.preprocess_input will convert the input images from RGB to BGR, then will zero-center each color channel with respect to the ImageNet dataset, without scaling.

[ ]:
```
# from above, found this last minute not sure if needed
# More experimentation could be done here to see if results are better
# tf.keras.applications.resnet.preprocess_input
```

[ ]:
```
# Create model
resnet_model = create_model(resnet_url)

# Compile
resnet_model.compile(loss='categorical_crossentropy',
                     optimizer=tf.keras.optimizers.Adam(),
                     metrics=['accuracy'])
```

```
# Fit the model
resnet_history = resnet_model.fit(train_ds,
                                  epochs=5,
                                  steps_per_epoch=len(train_ds),
                                  validation_data=val_ds,
                                  validation_steps=len(val_ds))
```

```
Epoch 1/5
355/355 [==============================] - 51s 111ms/step - loss: 0.8738 -
accuracy: 0.7449 - val_loss: 0.6888 - val_accuracy: 0.7958
Epoch 2/5
355/355 [==============================] - 38s 106ms/step - loss: 0.3914 -
accuracy: 0.8807 - val_loss: 0.6547 - val_accuracy: 0.7981
Epoch 3/5
355/355 [==============================] - 38s 107ms/step - loss: 0.2345 -
accuracy: 0.9306 - val_loss: 0.6738 - val_accuracy: 0.8040
Epoch 4/5
355/355 [==============================] - 38s 107ms/step - loss: 0.1425 -
accuracy: 0.9596 - val_loss: 0.6966 - val_accuracy: 0.8099
Epoch 5/5
355/355 [==============================] - 38s 106ms/step - loss: 0.0801 -
accuracy: 0.9825 - val_loss: 0.7239 - val_accuracy: 0.8110
```

[ ]:
```
res = resnet_model.evaluate(test_val_ds)
print("result: ", res)
```

```
62/62 [==============================] - 6s 93ms/step - loss: 0.6602 - accuracy:
0.8332
result:  [0.6602268815040588, 0.8331653475761414]
```

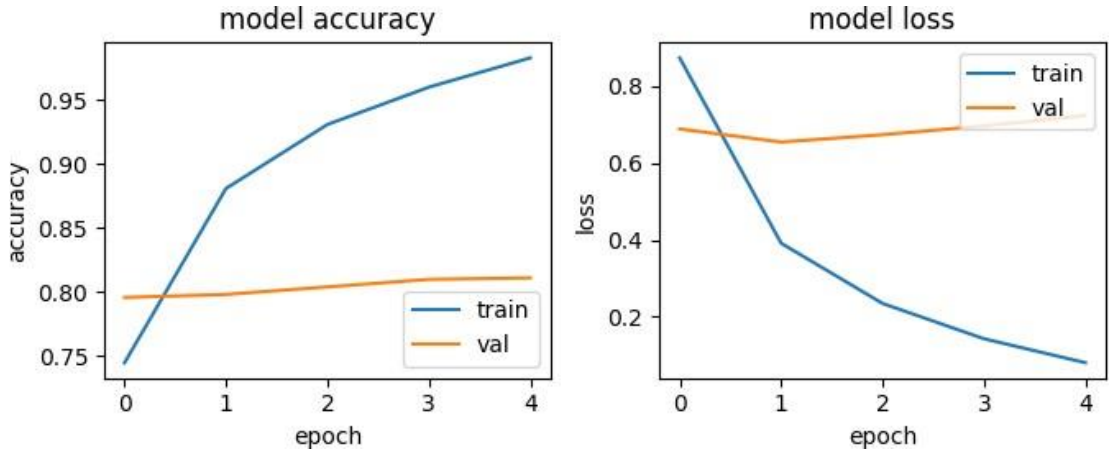
[ ]:
```
resnet_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 224, 224, 3)       0

 feature_extraction_layer (  (None, 2048)              23564800
 KerasLayer)

 dense (Dense)               (None, 128)               262272

 output_layer (Dense)        (None, 22)                2838

=================================================================
Total params: 23829910 (90.90 MB)
```

```
Trainable params: 265110 (1.01 MB)
Non-trainable params: 23564800 (89.89 MB)
_________________________________________________________________
```

[ ]:
```
resnet_model.save('model_resnet_v2_50.keras')
```

[ ]:
```
# Learning curve of the model training model
def learning_curve(hist):
  plt.figure(figsize=(7, 3))
  plt.subplot(1,2,1)
  plt.plot(hist.history['accuracy'])
  plt.plot(hist.history['val_accuracy'])
  plt.title('model accuracy')
  plt.ylabel('accuracy')
  plt.xlabel('epoch')
  plt.legend(['train', 'val'], loc='lower right')

  plt.subplot(1,2,2)
  plt.plot(hist.history['loss'])
  plt.plot(hist.history['val_loss'])
  plt.title('model loss')
  plt.ylabel('loss')
  plt.xlabel('epoch')
  plt.legend(['train', 'val'], loc='upper right')
  plt.tight_layout()
learning_curve(resnet_history)
```



[ ]:
```
# Retrieve an Image

def predict_on_image_batches(ds, count=1, batch_size=BATCH_SIZE):
```

```
  image_batch, label_batch = next(iter(ds.shuffle(buffer_size=BATCH_SIZE).
 ↪take(count)))
  # print("image batch shape", image_batch.shape)

  # # Preprocess the Image
  # image = image_batch[0].numpy()
  # batch_img = tf.reshape(image,[1, IMAGE_SIZE[0], IMAGE_SIZE[1], 3] )
  # print("reshaped batch image shape", batch_img.shape)

  # # processing label batch
  # true_label = categories[np.argmax(label_batch[0].numpy())]
  # true_label_index = np.argmax(label_batch[0].numpy())
  # true_label = categories[true_label_index]

  # # Make Prediction
  # batch_pred = resnet_model.predict(batch_img)#
  pred = batch_pred[0]

  # # Post-process Predictions
  # predicted_label_index = np.argmax(pred)
  # predicted_label = categories[predicted_label_index]

  # Above is working / experimenting below with multiple images

  # Preprocess the Batch of Images
  batch_img = tf.reshape(image_batch, [batch_size, IMAGE_SIZE[0],
 ↪IMAGE_SIZE[1], 3])
  # print("reshaped batch image shape", batch_img.shape)

  # Processing Label Batch
  true_labels = [categories[np.argmax(label.numpy())] for label in label_batch]

  # Make Predictions
  batch_pred = resnet_model.predict(batch_img)
  predicted_labels = [categories[np.argmax(pred)] for pred in batch_pred]

  return batch_img, true_labels, batch_pred, predicted_labels


predict_on_image_batches(test_val_ds, 1)
```

[ ]:
```
# Prediction on multiple
prediction_count = 10
batch_img, true_labels, batch_pred, predicted_labels =
 ↪predict_on_image_batches(test_val_ds, prediction_count)
```

```
1/1 [==============================] - 0s 48ms/step
```

In this below we have 9/10 predictions correct, image 9 mislabeling a football image as a cricket image. (image 10 not seen)

[ ]:
```
# Visualization loop
rows = 3  # Number of rows in the grid
cols = 3  # Number of columns in the grid
prediction_count = min(BATCH_SIZE, rows * cols)  # Ensure not to exceed the available predictions

plt.figure(figsize=(10, 10))

for i in range(prediction_count):
    # Display the input image
    sample_image = batch_img[i].numpy()
    sample_image_resized = cv2.resize(sample_image, (IMAGE_SIZE[0], IMAGE_SIZE[1]))
    sample_image_rescaled = sample_image_resized / 255.0
    # colored_img = cv2.cvtColor(sample_image_resized, cv2.COLOR_BGR2RGB)
    plt.subplot(rows, cols, i + 1)
    plt.imshow(sample_image_rescaled)
    plt.title(f"True: {true_labels[i]}\nPredicted: {predicted_labels[i]}")
    plt.axis("off")
```

Appendix C

Some outputs have been suppressed for clarity

[ ]: Object Detection - YOLOv8

```
#Clone yolo 8 and check all dependencies
!pip install ultralytics
import ultralytics
ultralytics.checks()
```

Ultralytics YOLOv8.0.225 Python-3.10.12 torch-2.1.0+cu118 CUDA:0 (Tesla T4, 15102MiB)

Setup complete (2 CPUs, 12.7 GB RAM, 27.9/78.2 GB disk)

[ ]:
```
#Train YOLO8 model
from ultralytics import YOLO
model = YOLO("yolov8n.yaml")
model = YOLO("yolov8n.pt")
model.train(data="coco128.yaml", epochs=3, verbose=False)
```

[ ]:
```
#Test model on images from test dataset
from IPython.display import Image
metrics = model.val()
```

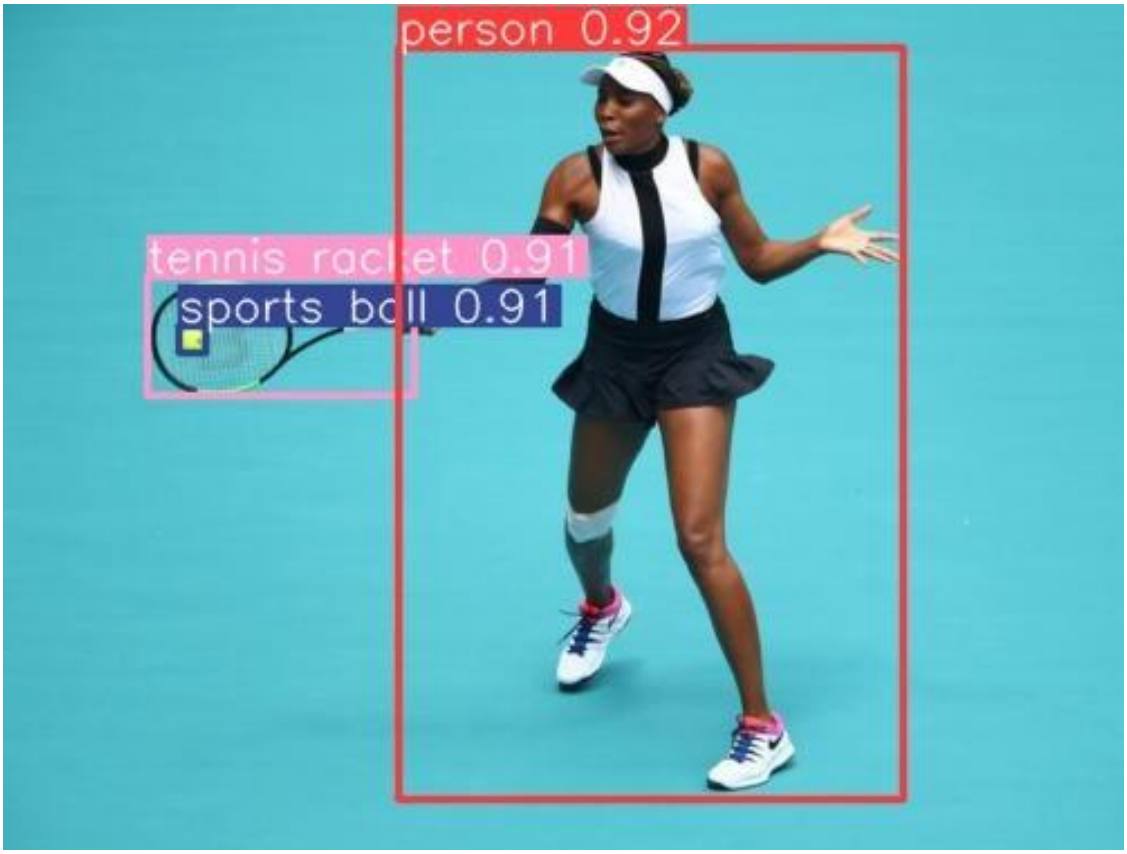
```
Ultralytics YOLOv8.0.225 Python-3.10.12 torch-2.1.0+cu118 CUDA:0 (Tesla T4, 15102MiB)
Model summary (fused): 168 layers, 3151904 parameters, 0 gradients, 8.7 GFLOPs
val: Scanning /content/datasets/coco128/labels/train2017.cache...
126 images, 2 backgrounds, 0 corrupt: 100%|        | 128/128 [00:00<?, ?it/s]
                 Class     Images  Instances      Box(P          R      mAP50
mAP50-95): 100%|        | 8/8 [00:07<00:00,  1.13it/s]
                   all        128        929      0.665      0.546      0.625
0.463
Speed: 0.4ms preprocess, 13.5ms inference, 0.0ms loss, 6.4ms postprocess per
image
Results saved to runs/detect/train2
```

[ ]:
```
def obj_det(image_path):
  results = model(source=image_path,save=True, save_txt=True, project='runs/
 ↪detect', name='predict', exist_ok=True)
  N = 12
  img_numb = image_path[-N:]
  return Image(filename='/content/runs/detect/predict/'+img_numb,width=600)
```

[ ]:
```
obj_det('/content/kaggle_data/data/tennis/00000007.jpg')
```

```
Results saved to runs/detect/predict
1 label saved to runs/detect/predict/labels
```

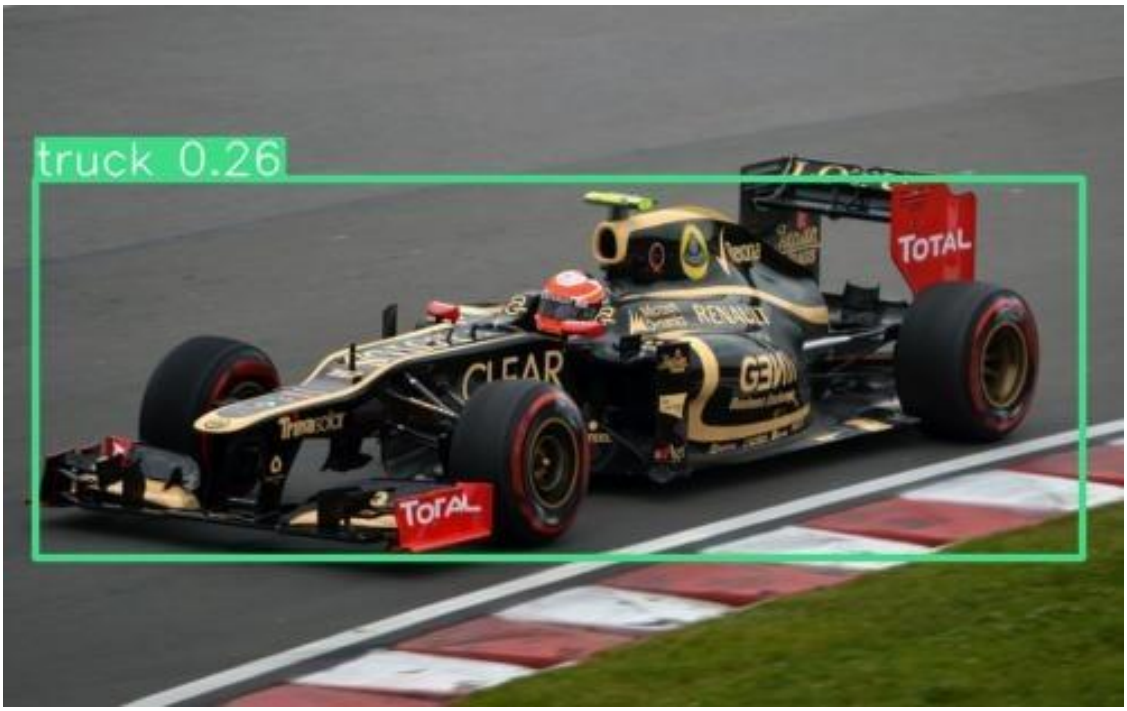
[ ]:



[ ]:
```
obj_det("/content/kaggle_data/data/formula1/00000023.jpg")
```

```
Results saved to runs/detect/predict
2 labels saved to runs/detect/predict/labels
```

[ ]:



[ ]:
```
obj_det("/content/kaggle_data/data/baseball/00000028.jpg")
```

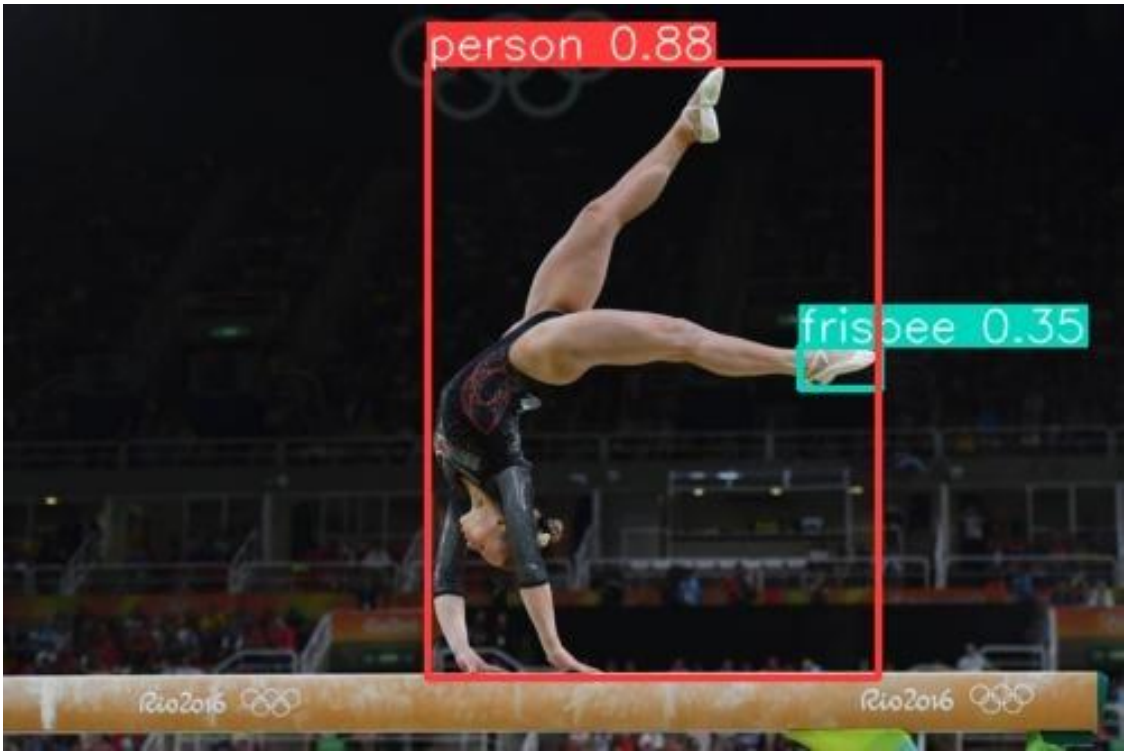
```
Results saved to runs/detect/predict
3 labels saved to runs/detect/predict/labels
```

[ ]:

[ ]:
```
obj_det('/content/kaggle_data/data/gymnastics/00000055.jpg')
```

```
Results saved to runs/detect/predict
4 labels saved to runs/detect/predict/labels
```

[ ]:



Object Detection - RetinaNet

[4]:
```
!git clone https://github.com/fizyr/keras-retinanet
```

```
Cloning into 'keras-retinanet'...
remote: Enumerating objects: 6224, done.
remote: Counting objects: 100% (19/19), done.
remote: Compressing objects: 100% (17/17), done.
remote: Total 6224 (delta 6), reused 9 (delta 2), pack-reused 6205
Receiving objects: 100% (6224/6224), 13.48 MiB | 20.76 MiB/s, done.
Resolving deltas: 100% (4207/4207), done.
```

[ ]:
```
%cd keras-retinanet
!pip install .
```

[6]:
```
!python /content/keras-retinanet/setup.py build_ext --inplace
```

```
/usr/local/lib/python3.10/dist-packages/setuptools/_init_.py:84:
_DeprecatedInstaller: setuptools.installer and fetch_build_eggs are deprecated.
!!

********************************************************************************
        Requirements should be satisfied by a PEP 517 installer.
        If you are using pip, you can try `pip install --use-pep517`.
```

```
**********************************************************************************

!!
  dist.fetch_build_eggs(dist.setup_requires)
running build_ext
copying build/lib.linux-x86_64-cpython-310/keras_retinanet/utils/compute_overlap
.cpython-310-x86_64-linux-gnu.so -> keras_retinanet/utils
```

[8]:
```
from tensorflow import keras
from keras_retinanet import models
from keras_retinanet.utils.image import read_image_bgr, preprocess_image,␣
↪resize_image
from keras_retinanet.utils.visualization import draw_box, draw_caption
from keras_retinanet.utils.colors import label_color
from keras_retinanet.utils.gpu import setup_gpu
import matplotlib.pyplot as plt
import cv2
import os
import numpy as np
import time
```

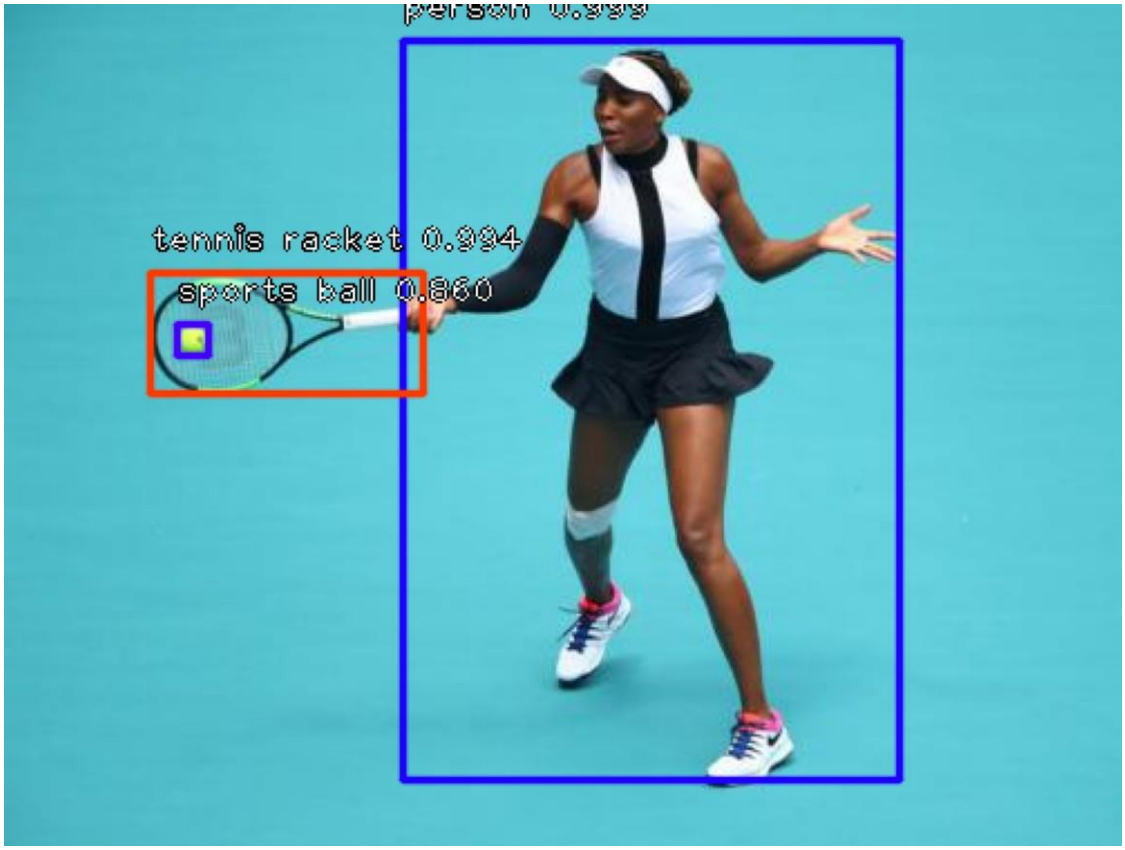
[9]:
```
#Load trained model and retinanet model and labels
model_path = os.path.join('/content/keras-retinanet', 'snapshots',␣
↪'resnet50_coco_best_v2.1.0.h5')
model = models.load_model(model_path, backbone_name='resnet50')
labels_to_names = {0: 'person', 1: 'bicycle', 2: 'car', 3: 'motorcycle', 4:␣
↪'airplane', 5: 'bus', 6: 'train', 7: 'truck', 8: 'boat', 9: 'traffic light',
                   10: 'fire hydrant', 11: 'stop sign', 12: 'parking meter', 13:
↪ 'bench', 14: 'bird', 15: 'cat', 16: 'dog', 17: 'horse', 18: 'sheep', 19:␣
↪'cow',
                   20: 'elephant', 21: 'bear', 22: 'zebra', 23: 'giraffe', 24:␣
↪'backpack', 25: 'umbrella', 26: 'handbag', 27: 'tie', 28: 'suitcase', 29:␣
↪'frisbee',
                   30: 'skis', 31: 'snowboard', 32: 'sports ball', 33: 'kite',␣
↪34: 'baseball bat', 35: 'baseball glove', 36: 'skateboard', 37: 'surfboard',␣
↪38: 'tennis racket', 39: 'bottle',
                   40: 'wine glass', 41: 'cup', 42: 'fork', 43: 'knife', 44:␣
↪'spoon', 45: 'bowl', 46: 'banana', 47: 'apple', 48: 'sandwich', 49: 'orange',
                   50: 'broccoli', 51: 'carrot', 52: 'hot dog', 53: 'pizza', 54:
↪ 'donut', 55: 'cake', 56: 'chair', 57: 'couch', 58: 'potted plant', 59:␣
↪'bed',
                   60: 'dining table', 61: 'toilet', 62: 'tv', 63: 'laptop', 64:
↪ 'mouse', 65: 'remote', 66: 'keyboard', 67: 'cell phone', 68: 'microwave',␣
↪69: 'oven',
                   70: 'toaster', 71: 'sink', 72: 'refrigerator', 73: 'book',␣
↪74: 'clock', 75: 'vase', 76: 'scissors', 77: 'teddy bear', 78: 'hair drier',␣
↪79: 'toothbrush'}
```

WARNING:tensorflow:No training configuration found in the save file, so the model was *not* compiled. Compile it manually.

[10]:
```
#Function to predict object classes
def retinanet_det(img_path):
  # load image
  image = read_image_bgr(img_path)

  # copy to draw on
  draw = image.copy()
  draw = cv2.cvtColor(draw, cv2.COLOR_BGR2RGB)

  # preprocess image for network
  image = preprocess_image(image)
  image, scale = resize_image(image)

  # process image
  start = time.time()
  boxes, scores, labels = model.predict_on_batch(np.expand_dims(image, axis=0))
  print("processing time: ", time.time() - start)

  # correct for image scale
  boxes /= scale

  # visualize detections
  for box, score, label in zip(boxes[0], scores[0], labels[0]):
      # scores are sorted so we can break
      if score < 0.5:
          break

      color = label_color(label)

      b = box.astype(int)
      draw_box(draw, b, color=color)

      caption = "{} {:.3f}".format(labels_to_names[label], score)
      draw_caption(draw, b, caption)
  plt.figure(figsize=(15, 15))
  plt.axis('off')
  plt.imshow(draw)
  plt.show()
```

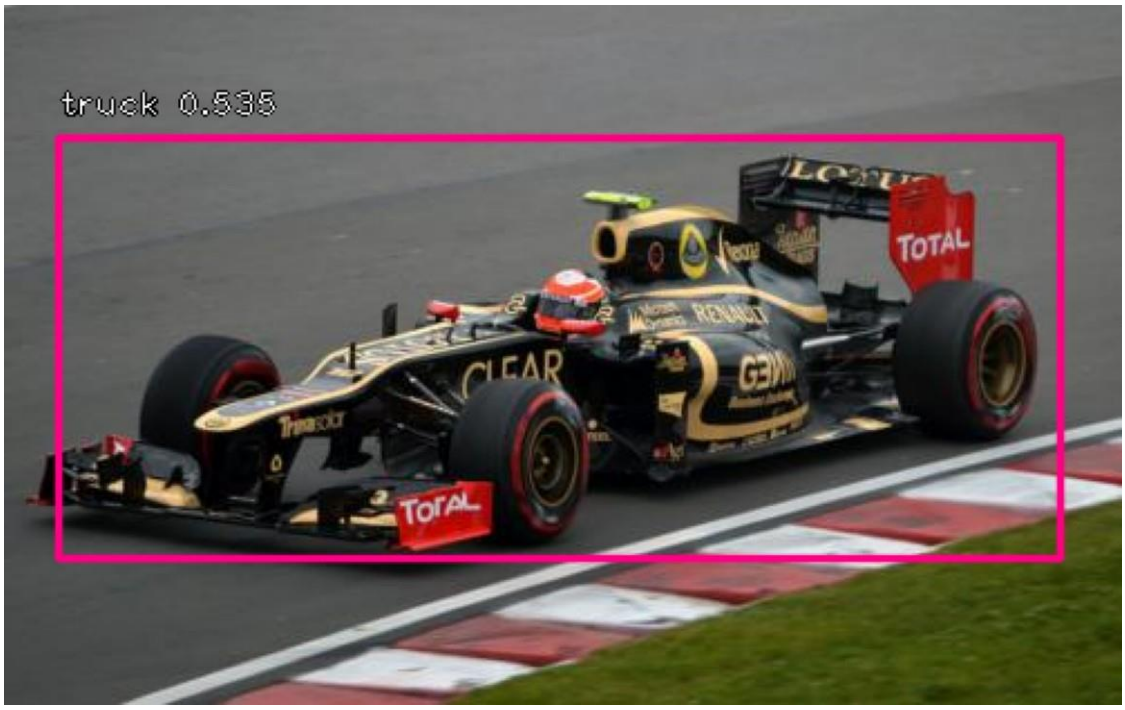
[11]:
```
retinanet_det('/content/kaggle_data/data/tennis/00000007.jpg')
```

processing time: 16.611504554748535



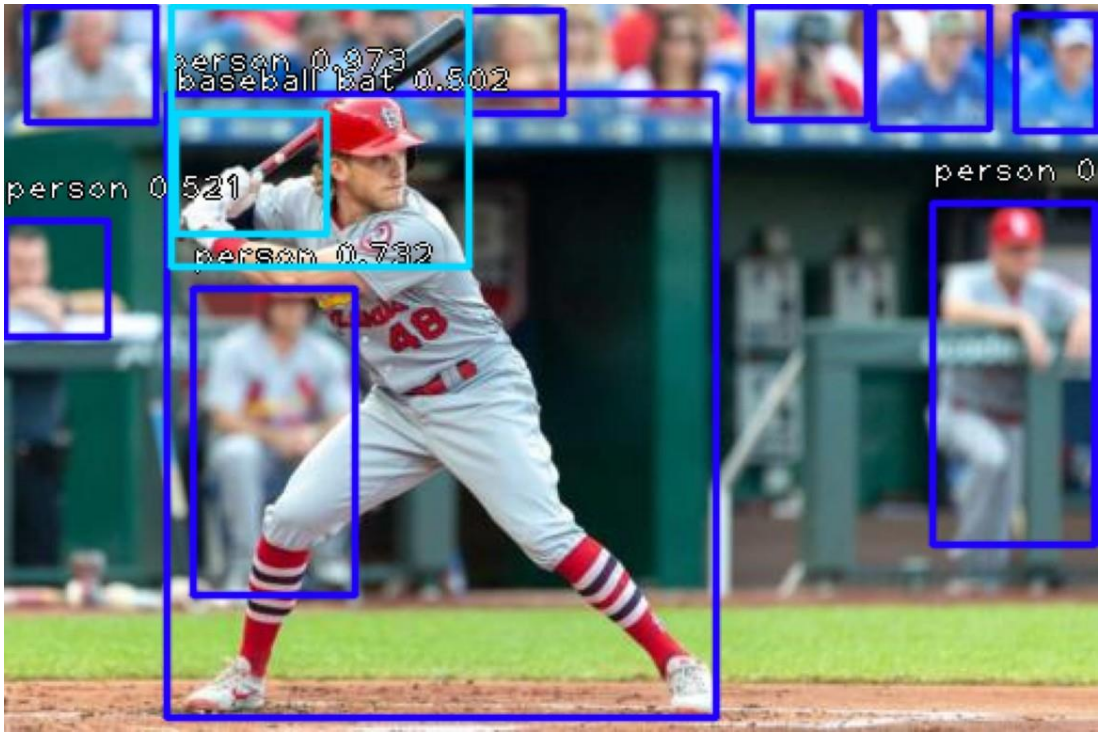
[12]:
```
retinanet_det("/content/kaggle_data/data/formula1/00000023.jpg")
```

processing time: 7.064410209655762



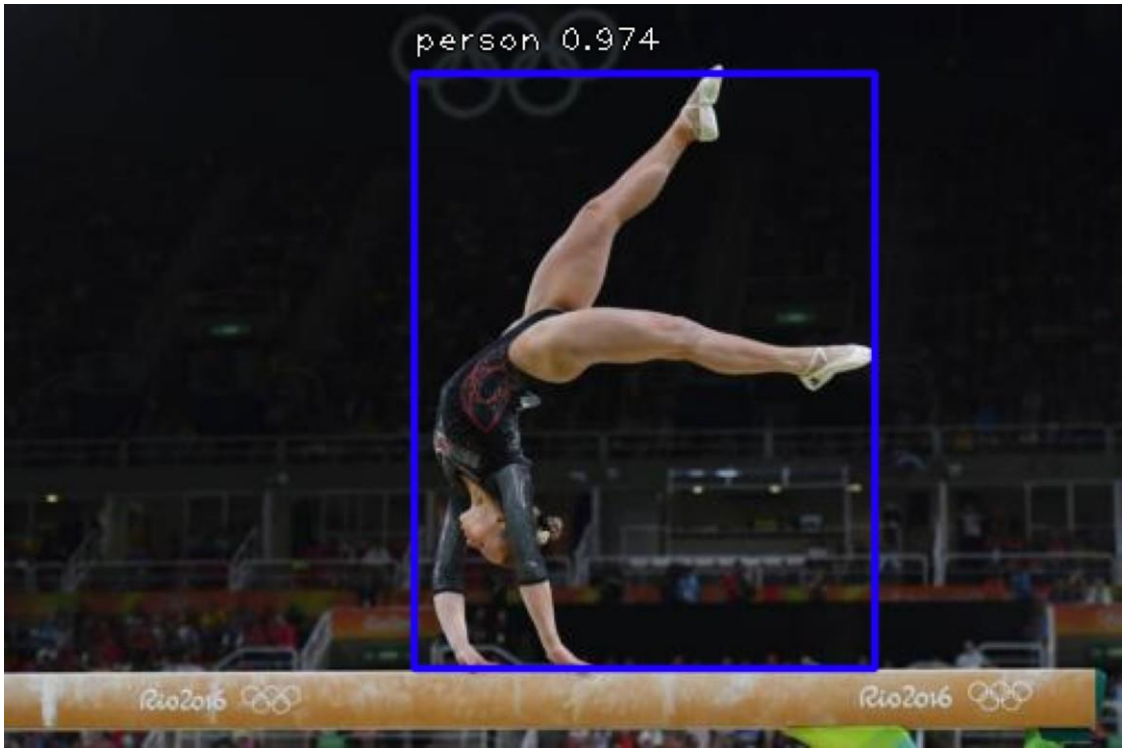
[13]:
```
retinanet_det("/content/kaggle_data/data/baseball/00000028.jpg")
```

processing time: 2.110607624053955



[14]:
```
retinanet_det("/content/kaggle_data/data/gymnastics/00000055.jpg")
```

```
processing time:  0.16313862800598145
```



0.1 Save with Pickle

Could be useful in saving model for application

[ ]:
```
#Optional Save the x and y
```

[ ]:
```
#dumping data into pickle file
#x_location = '/content/drive/MyDrive/Final_Project_AAI_521/data/x.pickle'
#y_location = '/content/drive/MyDrive/Final_Project_AAI_521/data/y.pickle'

#pickle file for features
#pickle_out = open(x_location,"wb") #path to save pickle file
#pickle.dump(x,pickle_out)
#pickle_out.close()

#pickle file for label
#pickle_out = open(y_location,"wb") #path to save pickle file
```

```
#pickle.dump(y,pickle_out)
#pickle_out.close()
```

[ ]:
```
#importing data (pickle) files x and y
#pickle_in = open(x_location,"rb")    #rb - read binary form #wb - Write binary form
#x   =   pickle.load(pickle_in)


#pickle_in = open(y_location,"rb")    #rb - read binary form #wb - Write binary form
#y   =   pickle.load(pickle_in)
```