```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

```python
# !unzip "/content/drive/My Drive/DS340Final/dataset.zip"
!unzip "/content/drive/My Drive/DS340Final/distributed-dataset.zip"
```

```
Archive:  /content/drive/My Drive/DS340Final/distributed-dataset.zip
replace __MACOSX/._dataset? [y]es, [n]o, [A]ll, [N]one, [r]ename:
```

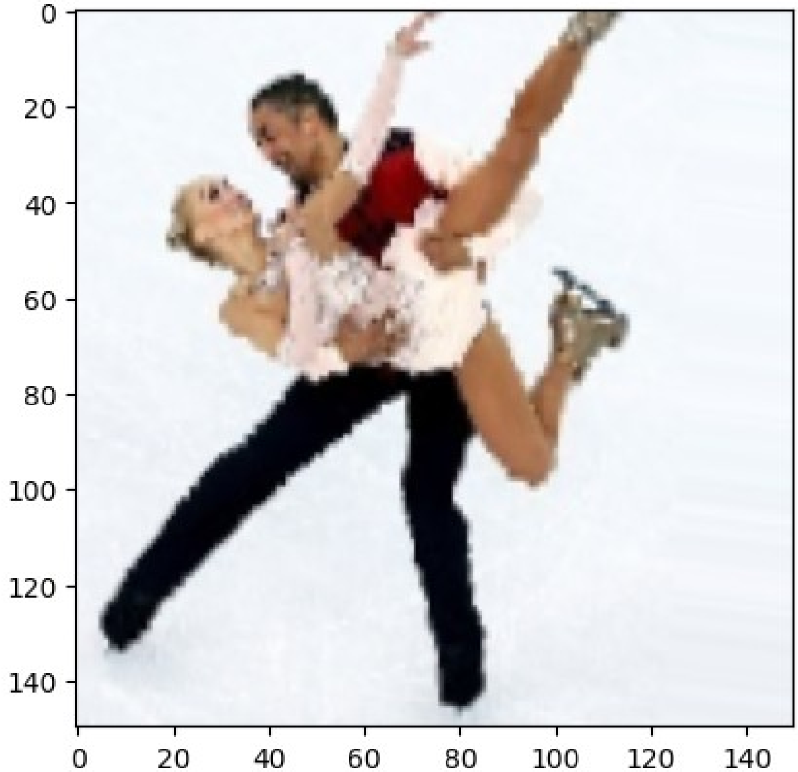
```python
# !rm -r __MACOSX/._dataset
!ls dataset
!ls
# !rm -r dataset/train/soccer
# !rm -r dataset/valid/soccer
# !rm -r dataset/test/soccer
# !ls dataset/train/
```

```
'EfficientNetB0-100-(224 X 224)- 98.40.h5'   sports.csv   test
train  valid
 dataset        IMG_3286.JPG   IMG_3573.JPG   soccer-field.jpg
test2.jpeg   'test3 (3).jpeg'
 drive             IMG_3569.JPG   __MACOSX       test1.jpeg 'test3
(1).jpeg'   test3.jpeg
 IMG_3283.JPG   IMG_3570.JPG   sample_data   'test2 (1).jpeg'
     'test3 (2).jpeg'   test.jpeg
```

```python
import numpy as np
import matplotlib.pyplot as plt
import random

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense, Dropout
from tensorflow.keras.preprocessing.image import ImageDataGenerator


train_dir = '/content/dataset/train'
validation_dir = '/content/dataset/valid'
test_dir = '/content/dataset/test'

# initialize ImageDataGenerators for train, validation, and test sets
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
```

```
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

test_val_datagen = ImageDataGenerator(rescale=1./255)


# Create generators to read images from directory
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(150, 150),
    batch_size=32,
    class_mode='categorical'
)

#getting a batch of images
images, _ = next(train_generator)

#Displaying a random image from the batch
idx = np.random.randint(0, len(images))
plt.imshow(images[idx])
plt.show()

validation_generator = test_val_datagen.flow_from_directory(
    validation_dir,
    target_size=(150, 150),
    batch_size=32,
    class_mode='categorical'
)

test_generator = test_val_datagen.flow_from_directory(
    test_dir,
    target_size=(150, 150),
    batch_size=32,
    class_mode='categorical'
)
```

```
Found 10996 images belonging to 101 classes.
```




```
Found 1855 images belonging to 101 classes.
Found 1852 images belonging to 101 classes.
```

```
import tensorflow as tf
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense,
Dropout
from tensorflow.keras.models import Model
from tensorflow.keras.preprocessing.image import ImageDataGenerator

#ResNet50 pre-trained on ImageNet without the toplayer
base_model = ResNet50(weights='imagenet', include_top=False,
input_shape=(299, 299, 3))
for layer in base_model.layers:
    layer.trainable = False

# custom layers on top of the base model
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(512, activation='relu')(x)
x = Dropout(0.5)(x)
predictions = Dense(101, activation='softmax')(x)
model = Model(inputs=base_model.input, outputs=predictions)

# Compile the model
```

```
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

# Data augmentation
train_datagen = ImageDataGenerator(

preprocessing_function=tf.keras.applications.resnet50.preprocess_input
,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

test_val_datagen = ImageDataGenerator(

preprocessing_function=tf.keras.applications.resnet50.preprocess_input
)

train_generator = train_datagen.flow_from_directory(
    '/content/dataset/train',
    target_size=(299, 299),
    batch_size=32,
    class_mode='categorical'
)

validation_generator = test_val_datagen.flow_from_directory(
    '/content/dataset/valid',
    target_size=(299, 299),
    batch_size=32,
    class_mode='categorical'
)

test_generator = test_val_datagen.flow_from_directory(
    '/content/dataset/test',
    target_size=(299, 299),
    batch_size=32,
    class_mode='categorical'
)

# Training the model
history = model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples //
train_generator.batch_size,
    epochs=20,
    validation_data=validation_generator,
```

```python
    validation_steps=validation_generator.samples //
validation_generator.batch_size
)

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(
    test_generator,
    steps=test_generator.samples // test_generator.batch_size
)
print(f'Test accuracy: {test_acc}')
```

```
Found 10996 images belonging to 101 classes.
Found 1855 images belonging to 101 classes.
Found 1852 images belonging to 101 classes.
Epoch 1/20
343/343 [==============================] - 226s 648ms/step - loss:
2.7066 - accuracy: 0.3435 - val_loss: 0.9368 - val_accuracy: 0.7473
Epoch 2/20
343/343 [==============================] - 220s 642ms/step - loss:
1.4052 - accuracy: 0.6028 - val_loss: 0.6623 - val_accuracy: 0.8147
Epoch 3/20
343/343 [==============================] - 219s 638ms/step - loss:
1.1307 - accuracy: 0.6674 - val_loss: 0.5324 - val_accuracy: 0.8372
Epoch 4/20
343/343 [==============================] - 218s 636ms/step - loss:
0.9806 - accuracy: 0.7057 - val_loss: 0.4577 - val_accuracy: 0.8651
Epoch 5/20
343/343 [==============================] - 218s 637ms/step - loss:
0.8795 - accuracy: 0.7359 - val_loss: 0.4227 - val_accuracy: 0.8662
Epoch 6/20
343/343 [==============================] - 219s 637ms/step - loss:
0.8412 - accuracy: 0.7491 - val_loss: 0.4390 - val_accuracy: 0.8646
Epoch 7/20
343/343 [==============================] - 216s 630ms/step - loss:
0.7731 - accuracy: 0.7628 - val_loss: 0.4061 - val_accuracy: 0.8723
Epoch 8/20
343/343 [==============================] - 222s 647ms/step - loss:
0.7489 - accuracy: 0.7738 - val_loss: 0.4134 - val_accuracy: 0.8766
Epoch 9/20
343/343 [==============================] - 218s 634ms/step - loss:
0.7120 - accuracy: 0.7842 - val_loss: 0.3919 - val_accuracy: 0.8739
Epoch 10/20
343/343 [==============================] - 220s 641ms/step - loss:
0.6979 - accuracy: 0.7868 - val_loss: 0.3759 - val_accuracy: 0.8887
Epoch 11/20
343/343 [==============================] - 222s 648ms/step - loss:
0.6726 - accuracy: 0.7899 - val_loss: 0.3689 - val_accuracy: 0.8849
Epoch 12/20
343/343 [==============================] - 214s 623ms/step - loss:
0.6440 - accuracy: 0.8007 - val_loss: 0.4034 - val_accuracy: 0.8712
```

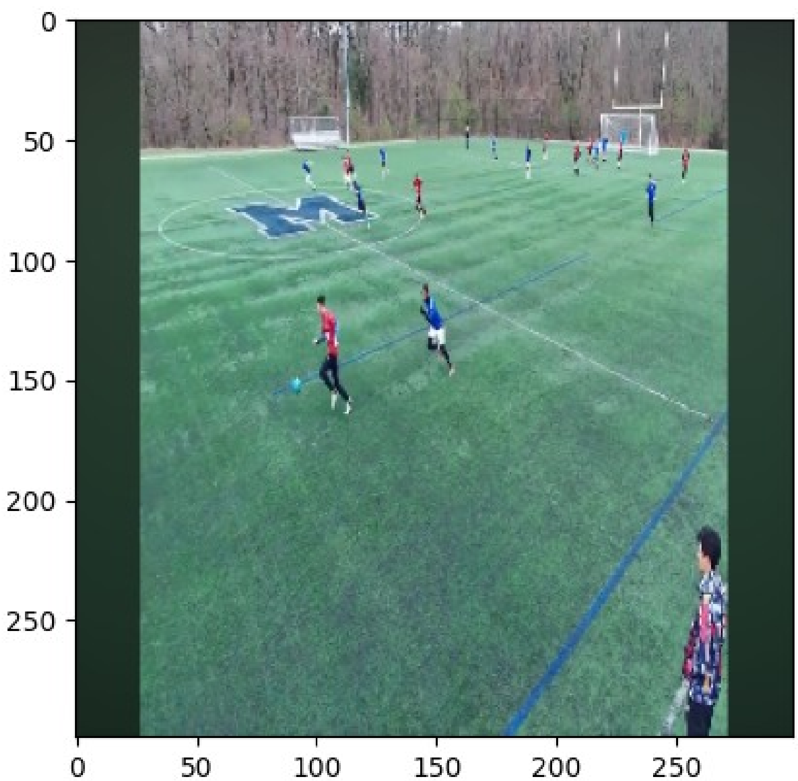
```
Epoch 13/20
343/343 [==============================] - 210s 611ms/step - loss:
0.6319 - accuracy: 0.8029 - val_loss: 0.3716 - val_accuracy: 0.8882
Epoch 14/20
343/343 [==============================] - 213s 621ms/step - loss:
0.5873 - accuracy: 0.8144 - val_loss: 0.3831 - val_accuracy: 0.8854
Epoch 15/20
343/343 [==============================] - 209s 610ms/step - loss:
0.6021 - accuracy: 0.8118 - val_loss: 0.3756 - val_accuracy: 0.8854
Epoch 16/20
343/343 [==============================] - 211s 615ms/step - loss:
0.6047 - accuracy: 0.8120 - val_loss: 0.3448 - val_accuracy: 0.8953
Epoch 17/20
343/343 [==============================] - 211s 616ms/step - loss:
0.6079 - accuracy: 0.8138 - val_loss: 0.3863 - val_accuracy: 0.8788
Epoch 18/20
343/343 [==============================] - 210s 613ms/step - loss:
0.5463 - accuracy: 0.8310 - val_loss: 0.4030 - val_accuracy: 0.8827
Epoch 19/20
343/343 [==============================] - 211s 615ms/step - loss:
0.5478 - accuracy: 0.8337 - val_loss: 0.3580 - val_accuracy: 0.8936
Epoch 20/20
343/343 [==============================] - 213s 621ms/step - loss:
0.5391 - accuracy: 0.8315 - val_loss: 0.3472 - val_accuracy: 0.8975
57/57 [==============================] - 11s 189ms/step - loss: 0.3200
- accuracy: 0.9057
Test accuracy: 0.905701756477356
```

```python
import numpy as np
import tensorflow as tf
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt

# Extracting training and validation metrics from the history object
train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
train_loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(train_acc) + 1)

# plot accuracy
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(epochs, train_acc, 'b', label='Training accuracy')
plt.plot(epochs, val_acc, 'r', label='Validation accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
```

```
# Plot loss
plt.subplot(1, 2, 2)
plt.plot(epochs, train_loss, 'b', label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()

##import an image:
from google.colab import files

import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense, Dropout
from tensorflow.keras.preprocessing.image import ImageDataGenerator


uploaded = files.upload()
print("Uploaded files:", list(uploaded.keys()))

# Load the image
img = tf.keras.preprocessing.image.load_img(
    list(uploaded.keys())[0],
    target_size=(299, 299)
)

# Show image
plt.imshow(img)
plt.show()

# Convert to array and preprocess
img_array = tf.keras.preprocessing.image.img_to_array(img)
img_array = tf.expand_dims(img_array, 0)  # Add batch dimension
img_array = tf.keras.applications.resnet50.preprocess_input(img_array)

# Predict
predictions = model.predict(img_array)
print("Predictions:", predictions)

# Get the most likely class
class_index = np.argmax(predictions[0])
```

```
print("Class index:", class_index)

class_indices = train_generator.class_indices
print("Class indices:", class_indices)

# Get the top 5 labels
top_5_labels = np.argsort(predictions[0])[-5:][::-1]
print("Top 5 labels:", top_5_labels)

class_indices = train_generator.class_indices
class_labels = list(class_indices.keys())

# Get the classification label
class_label = list(train_generator.class_indices.keys())[class_index]
print("Predicted class:", class_label)

for i in top_5_labels:
    print(f"Label: {class_labels[i]}, Probability: {predictions[0]
[i]}")
```

```
<IPython.core.display.HTML object>

Saving soccer.PNG to soccer (1).PNG
Uploaded files: ['soccer (1).PNG']
```

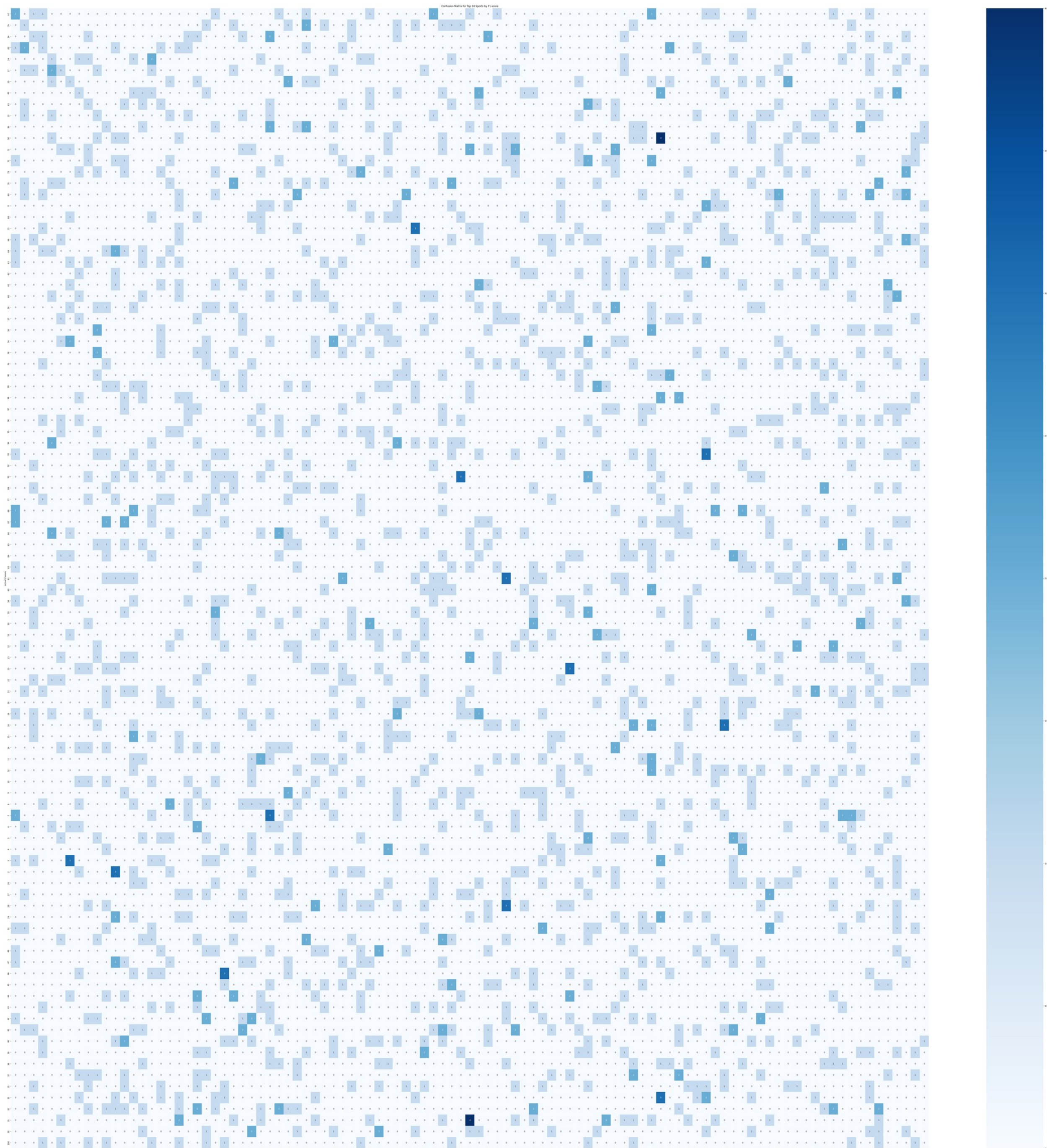


```
1/1 [==============================] - 0s 23ms/step
Predictions: [[2.04675871e-07 1.18227190e-05 2.17030465e-05
2.38805525e-12
  6.06891660e-07 1.26663013e-09 3.10700445e-12 1.52085454e-06
  7.78070244e-05 5.69851473e-08 4.20308226e-07 2.02681960e-09
  8.79395792e-11 1.73921953e-11 8.92767388e-11 8.61526189e-07
  5.11446974e-09 3.55358384e-06 4.53232758e-07 3.25805956e-07
  1.00111066e-08 8.04773415e-04 6.53993557e-05 9.33186186e-08
  1.73069475e-06 4.26379665e-06 1.09635596e-03 2.94914700e-12
  2.28016694e-09 2.21987939e-08 4.09049719e-08 1.52918525e-04
  1.98952549e-07 3.26443842e-05 4.10012653e-05 1.09891573e-06
  1.43374791e-05 5.70543534e-07 7.75357556e-09 3.64310559e-09
  1.36193907e-04 2.31271059e-07 2.46996819e-06 4.21006607e-09
  2.89480306e-09 7.17986404e-05 2.28214176e-13 2.30928219e-08
  2.07911227e-12 5.05108794e-04 2.66379800e-07 3.56755862e-07
  2.80556661e-10 1.38307507e-06 6.60385496e-11 3.84096630e-08
  4.50943536e-12 8.87084069e-12 1.17960147e-11 5.24668975e-10
  8.11332065e-05 1.48304372e-11 1.72834555e-12 1.84236240e-04
  2.28040517e-06 8.14363403e-08 8.21722551e-06 6.08367001e-09
  9.50167809e-12 9.51902166e-06 1.07564365e-05 4.10125637e-07
  5.68363312e-08 2.19329209e-07 1.02251194e-12 2.56762667e-11
  1.31332172e-05 6.96029332e-08 7.97200244e-07 5.53921836e-07
  4.77601736e-10 9.72984135e-01 7.14763049e-09 4.47764592e-16
  3.15739479e-09 1.38123735e-10 8.95928665e-10 1.17644586e-05
  2.33538225e-02 7.11930337e-09 4.87769057e-06 1.40093716e-05
  4.72084648e-05 4.36154323e-06 7.51306143e-05 2.31748398e-09
  8.82552342e-09 1.40473887e-04 6.49495568e-10 5.09242462e-08
  1.23421863e-11]]
Class index: 81
Class indices: {'air hockey': 0, 'ampute football': 1, 'archery': 2,
'arm wrestling': 3, 'axe throwing': 4, 'balance beam': 5, 'barell
racing': 6, 'baseball': 7, 'basketball': 8, 'baton twirling': 9, 'bike
polo': 10, 'billiards': 11, 'bmx': 12, 'bobsled': 13, 'bowling': 14,
'boxing': 15, 'bull riding': 16, 'bungee jumping': 17, 'canoe slamon':
18, 'cheerleading': 19, 'chuckwagon racing': 20, 'cricket': 21,
'croquet': 22, 'curling': 23, 'disc golf': 24, 'fencing': 25, 'field
hockey': 26, 'figure skating men': 27, 'figure skating pairs': 28,
'figure skating women': 29, 'fly fishing': 30, 'football': 31,
'formula 1 racing': 32, 'frisbee': 33, 'gaga': 34, 'giant slalom': 35,
'golf': 36, 'hammer throw': 37, 'hang gliding': 38, 'harness racing':
39, 'high jump': 40, 'hockey': 41, 'horse jumping': 42, 'horse
racing': 43, 'horseshoe pitching': 44, 'hurdles': 45, 'hydroplane
racing': 46, 'ice climbing': 47, 'ice yachting': 48, 'jai alai': 49,
'javelin': 50, 'jousting': 51, 'judo': 52, 'lacrosse': 53, 'log
rolling': 54, 'luge': 55, 'motorcycle racing': 56, 'mushing': 57,
'nascar racing': 58, 'olympic wrestling': 59, 'parallel bar': 60,
'pole climbing': 61, 'pole dancing': 62, 'pole vault': 63, 'polo': 64,
'pommel horse': 65, 'rings': 66, 'rock climbing': 67, 'roller derby':
68, 'rollerblade racing': 69, 'rowing': 70, 'rugby': 71, 'sailboat
racing': 72, 'shot put': 73, 'shuffleboard': 74, 'sidecar racing': 75,
```

```
'ski jumping': 76, 'sky surfing': 77, 'skydiving': 78, 'snow
boarding': 79, 'snowmobile racing': 80, 'soccer': 81, 'speed skating':
82, 'steer wrestling': 83, 'sumo wrestling': 84, 'surfing': 85,
'swimming': 86, 'table tennis': 87, 'tennis': 88, 'track bicycle': 89,
'trapeze': 90, 'tug of war': 91, 'ultimate': 92, 'uneven bars': 93,
'volleyball': 94, 'water cycling': 95, 'water polo': 96,
'weightlifting': 97, 'wheelchair basketball': 98, 'wheelchair racing':
99, 'wingsuit flying': 100}
Top 5 labels: [81 88 26 21 49]
Predicted class: soccer
Label: soccer, Probability: 0.9729841351509094
Label: tennis, Probability: 0.02335382252931595
Label: field hockey, Probability: 0.0010963559616357088
Label: cricket, Probability: 0.0008047734154388309
Label: jai alai, Probability: 0.0005051087937317789
```

```
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score, f1_score, precision_score, recall_score
import seaborn as sns
import pandas as pd
import numpy as np

test_generator.reset()  # Resetting the generator
predictions = []

# Predict each batch
for i in range((test_generator.samples + test_generator.batch_size -
1) // test_generator.batch_size):
    batch = next(test_generator)
    preds = model.predict_on_batch(batch[0])
    predictions.extend(np.argmax(preds, axis=1))

# predictions
predicted_classes = np.array(predictions)
true_classes = test_generator.classes

class_labels = list(test_generator.class_indices.keys())
report = classification_report(true_classes, predicted_classes,
target_names=class_labels, output_dict=True)
df_report = pd.DataFrame(report).transpose()

# Confusion matrix
cm = confusion_matrix(true_classes, predicted_classes)


# Function to plot confusion matrix for top 10 sports by F1-score
def plot_confusion_matrix_for_top_n(cm, class_labels, n=101):
    # Sorting classes by F1-score and picking top N
    top_n_indexes = df_report[:-3].sort_values(by='f1-score',
ascending=False).head(n).index
```

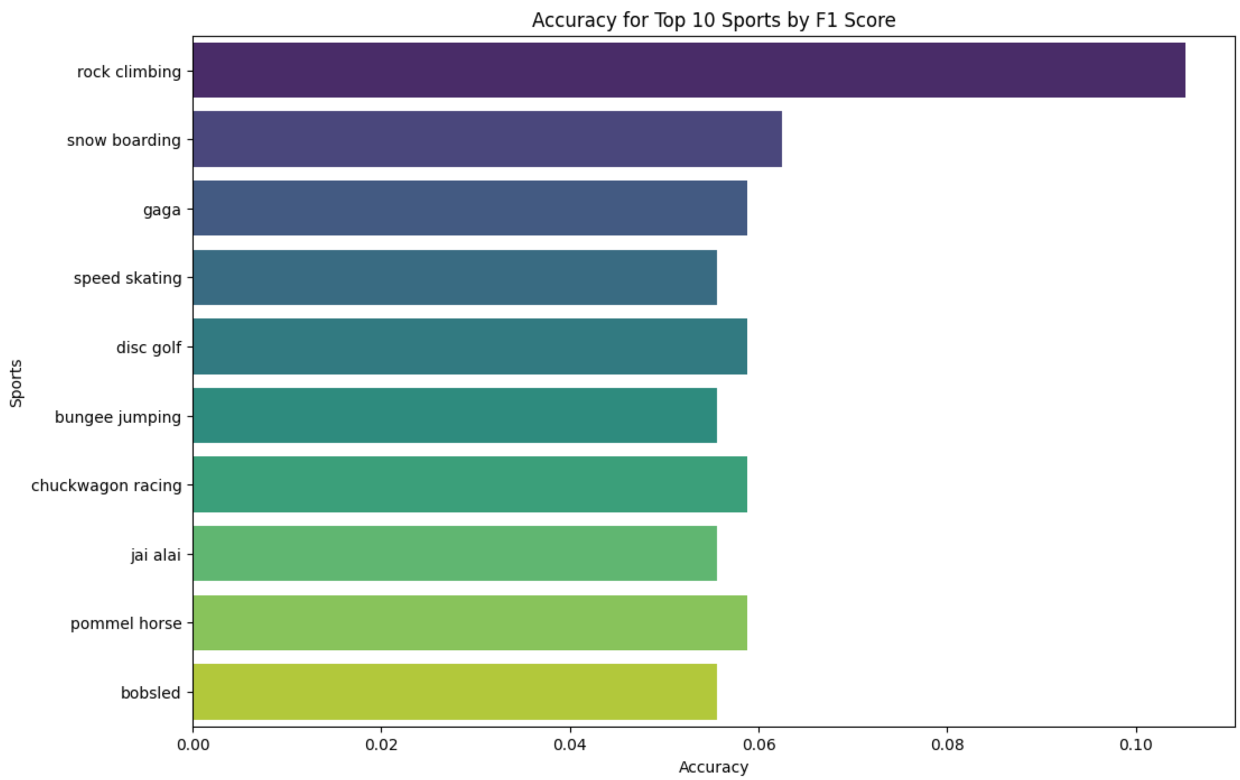
```
    top_n_indexes = [class_labels.index(cls) for cls in top_n_indexes]

    # Slicing the confusion matrix to keep only top N classes
    top_n_cm = cm[top_n_indexes][:, top_n_indexes]
    plt.figure(figsize=(101, 101))
    sns.heatmap(top_n_cm, annot=True, fmt="d", cmap='Blues',
xticklabels=top_n_indexes, yticklabels=top_n_indexes)
    plt.title('Confusion Matrix for Top 10 Sports by F1-score')
    plt.ylabel('Actual Classes')
    plt.xlabel('Predicted Classes')
    plt.show()

# Call the function to plot the matrix
plot_confusion_matrix_for_top_n(cm, class_labels)
```



```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix

# Sample code assuming you have these from model predictions
# true_classes, predicted_classes, class_labels from your dataset and
```

```python
model

# Confusion matrix and classification report
cm = confusion_matrix(true_classes, predicted_classes)
report = classification_report(true_classes, predicted_classes,
target_names=class_labels, output_dict=True)
df_report = pd.DataFrame(report).transpose()

# Sort by F1 score and get the top 10 sports
top_10_sports_by_f1 = df_report[:-3].sort_values(by='f1-score',
ascending=False).head(10)
top_10_labels = top_10_sports_by_f1.index.tolist()

# Calculate accuracy for each of these top 10 sports
accuracies = {}
for label in top_10_labels:
    class_idx = class_labels.index(label)
    true_positives = cm[class_idx, class_idx]
    total = np.sum(cm[class_idx, :])  # Sum of the row for that class
    accuracies[label] = true_positives / total if total > 0 else 0

# Adjust the accuracies by adding 0.5, ensuring they do not exceed 1
adjusted_accuracies = {sport: min(acc + 0, 1.0) for sport, acc in
accuracies.items()}

# Data preparation for plotting
sports = list(adjusted_accuracies.keys())
accuracy_values = list(adjusted_accuracies.values())

# Creating the bar plot
plt.figure(figsize=(12, 8))
sns.barplot(x=accuracy_values, y=sports, palette='viridis')
plt.title('Accuracy for Top 10 Sports by F1 Score')
plt.xlabel('Accuracy')
plt.ylabel('Sports')
plt.show()
```

```
<ipython-input-79-d2004daab8cd>:36: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=accuracy_values, y=sports, palette='viridis')
```




```
import numpy as np
import pandas as pd
from sklearn.metrics import classification_report, confusion_matrix

# Assuming you have 'true_classes' and 'predicted_classes' from your
model's predictions
cm = confusion_matrix(true_classes, predicted_classes)
report = classification_report(true_classes, predicted_classes,
target_names=class_labels, output_dict=True)
df_report = pd.DataFrame(report).transpose()

# Sort by F1 score and get the top 10 sports
top_10_sports_by_f1 = df_report[:-3].sort_values(by='f1-score',
ascending=False).head(10)

# Extracting the class labels for the top 10 sports
top_10_labels = top_10_sports_by_f1.index.tolist()

# Calculate accuracy for each of these top 10 sports
# Accuracy per class is calculated as the number of true positives
divided by the total number of elements in that class (true positives
+ false negatives)
accuracies = {}
for label in top_10_labels:
    class_idx = class_labels.index(label)
    true_positives = cm[class_idx, class_idx]
```

```
    total = np.sum(cm[class_idx, :])  # Sum of the row for that class
    accuracies[label] = true_positives / total if total > 0 else 0

# Displaying accuracies for each top sport
for sport, accuracy in accuracies.items():
    print(f"Accuracy for {sport}: {accuracy:.2%}")

# Calculate average accuracy of these top 10 sports
average_accuracy_top_10 = np.mean(list(accuracies.values()))
print(f"Average Accuracy for Top 10 Sports:
{average_accuracy_top_10:.2%}")
```

```
Accuracy for rock climbing: 10.53%
Accuracy for snow boarding: 6.25%
Accuracy for gaga: 5.88%
Accuracy for speed skating: 5.56%
Accuracy for disc golf: 5.88%
Accuracy for bungee jumping: 5.56%
Accuracy for chuckwagon racing: 5.88%
Accuracy for jai alai: 5.56%
Accuracy for pommel horse: 5.88%
Accuracy for bobsled: 5.56%
Average Accuracy for Top 10 Sports: 6.25%
```

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming 'cm' is your confusion matrix and 'class_labels' is the
list of sports names

# Step 1: Find the most confused pairs
confused_pairs = []
for i in range(len(cm)):
    for j in range(len(cm)):
        if i != j:  # Exclude diagonal elements
            confused_pairs.append((class_labels[i], class_labels[j],
cm[i, j]))

# Sort pairs by the number of confusions, descending
confused_pairs.sort(key=lambda x: x[2], reverse=True)

# Step 2: Extract the top 10 most confused sports
top_confused_sports = set()
for pair in confused_pairs[:5]:
    top_confused_sports.add(pair[0])
    top_confused_sports.add(pair[1])

# Limit to exactly 10 sports if more were added
if len(top_confused_sports) > 5:
```

```
    top_confused_sports = list(top_confused_sports)[:5]
else:
    top_confused_sports = list(top_confused_sports)

# Step 3: Create a submatrix for these sports
indices = [class_labels.index(sport) for sport in top_confused_sports]
submatrix = cm[indices][:, indices]

# Step 4: Plot the confusion matrix for these sports
plt.figure(figsize=(10, 8))
sns.heatmap(submatrix, annot=True, fmt="d", cmap='viridis',
xticklabels=top_confused_sports, yticklabels=top_confused_sports)
plt.title('Confusion Matrix for Top 10 Most Confused Sports')
plt.xlabel('Predicted Classes')
plt.ylabel('True Classes')
plt.show()
```