```
!pip install pafy youtube-dl moviepy
!pip install imageio-ffmpeg
!pip3 install imageio==2.4.1
```

tf.random.set_seed(seed_constant)

Looking in indexes: https://us-python.pkg.dev/colab-wheels/pub
Requirement already satisfied: pafy in /usr/local/lib/python3.7/dist-packages (0.5.5)
Requirement already satisfied: youtube-dl in /usr/local/lib/python3.7/dist-packages (0.2.3
Requirement already satisfied: moviepy in /usr/local/lib/python3.7/dist-packages (0.2.3
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from movequirement already satisfied: tqdm<5.0,>=4.0.2 in /usr/local/lib/python3.7/dist-packages (from movequirement already satisfied: imageio<3.0,>=2.1.2 in /usr/local/lib/python3.7/dist-package (from indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/pub
Requirement already satisfied: imageio-ffmpeg in /usr/local/lib/python3.7/dist-packages Requirement already satisfied: imageio=2.4.1 in /usr/local/lib/python3.7/dist-packages Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from imageio=2.4.1 in /usr/local/lib/python3.7/dist-packages (from im

```
# Import the required libraries.
import os
import cv2
import pafy
import math
import random
import numpy as np
import datetime as dt
import tensorflow as tf
from collections import deque
import matplotlib.pyplot as plt
from moviepy.editor import *
%matplotlib inline
from sklearn.model selection import train test split
from tensorflow.keras.layers import *
from tensorflow.keras.models import Sequential
from tensorflow.keras.utils import to categorical
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import plot model
seed constant = 27
np.random.seed(seed constant)
random.seed(seed constant)
```

```
# Discard the output of this cell.
%%capture
# Downland the UCF50 Dataset
!wget --no-check-certificate https://www.crcv.ucf.edu/data/UCF50.rar
#Extract the Dataset
!unrar x UCF50.rar
plt.figure(figsize = (20, 20))
# Get the names of all classes/categories in UCF50.
all classes names = os.listdir('UCF50')
# Generate a list of 20 random values. The values will be between 0-50,
# where 50 is the total number of class in the dataset.
random range = random.sample(range(len(all classes names)), 20)
# Iterating through all the generated random values.
for counter, random index in enumerate(random range, 1):
    # Retrieve a Class Name using the Random Index.
    selected_class_Name = all_classes_names[random_index]
    # Retrieve the list of all the video files present in the randomly selected Class Directo
    video_files_names_list = os.listdir(f'UCF50/{selected_class_Name}')
    # Randomly select a video file from the list retrieved from the randomly selected Class D
    selected video file name = random.choice(video files names list)
    # Initialize a VideoCapture object to read from the video File.
    video reader = cv2.VideoCapture(f'UCF50/{selected class Name}/{selected video file name}'
    # Read the first frame of the video file.
    , bgr frame = video reader.read()
    # Release the VideoCapture object.
    video reader.release()
    # Convert the frame from BGR into RGB format.
    rgb_frame = cv2.cvtColor(bgr_frame, cv2.COLOR_BGR2RGB)
    # Write the class name on the video frame.
    cv2.putText(rgb frame, selected class Name, (10, 30), cv2.FONT HERSHEY SIMPLEX, 1, (255,
    # Display the frame.
    plt.subplot(5, 4, counter);plt.imshow(rgb frame);plt.axis('off')
```



















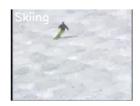






















```
# Specify the height and width to which each video frame will be resized in our dataset.
IMAGE HEIGHT , IMAGE WIDTH = 64, 64
# Specify the number of frames of a video that will be fed to the model as one sequence.
SEQUENCE LENGTH = 20
# Specify the directory containing the UCF50 dataset.
DATASET DIR = "UCF50"
# Specify the list containing the names of the classes used for training. Feel free to choose
CLASSES LIST = ["WalkingWithDog", "TaiChi", "Swing", "HorseRace"]
def frames extraction(video path):
   This function will extract the required frames from a video after resizing and normalizin
        video_path: The path of the video in the disk, whose frames are to be extracted.
   Returns:
       frames_list: A list containing the resized and normalized frames of the video.
   # Declare a list to store video frames.
   frames_list = []
   # Read the Video File using the VideoCapture object.
   video reader = cv2.VideoCapture(video path)
   # Get the total number of frames in the video.
   video_frames_count = int(video_reader.get(cv2.CAP_PROP_FRAME_COUNT))
   # Calculate the the interval after which frames will be added to the list.
   skip_frames_window = max(int(video_frames_count/SEQUENCE_LENGTH), 1)
   # Iterate through the Video Frames.
   for frame_counter in range(SEQUENCE_LENGTH):
        # Set the current frame position of the video.
       video_reader.set(cv2.CAP_PROP_POS_FRAMES, frame_counter * skip_frames_window)
        # Reading the frame from the video.
        success, frame = video_reader.read()
        # Check if Video frame is not successfully read then break the loop
        if not success:
            break
        # Resize the Frame to fixed height and width.
        resized frame = cv2.resize(frame, (IMAGE HEIGHT, IMAGE WIDTH))
        # Normalize the resized frame by dividing it with 255 so that each pixel value then 1
```

```
normalized frame = resized frame / 255
        # Append the normalized frame into the frames list
        frames list.append(normalized frame)
   # Release the VideoCapture object.
   video reader.release()
   # Return the frames list.
   return frames_list
def create_dataset():
   This function will extract the data of the selected classes and create the required datas
    Returns:
       features:
                          A list containing the extracted frames of the videos.
                           A list containing the indexes of the classes associated with the v
        labels:
       video_files_paths: A list containing the paths of the videos in the disk.
   # Declared Empty Lists to store the features, labels and video file path values.
   features = []
   labels = []
   video_files_paths = []
   # Iterating through all the classes mentioned in the classes list
   for class_index, class_name in enumerate(CLASSES_LIST):
        # Display the name of the class whose data is being extracted.
        print(f'Extracting Data of Class: {class_name}')
        # Get the list of video files present in the specific class name directory.
        files list = os.listdir(os.path.join(DATASET DIR, class name))
       # Iterate through all the files present in the files list.
        for file name in files list:
            # Get the complete video path.
            video_file_path = os.path.join(DATASET_DIR, class_name, file_name)
            # Extract the frames of the video file.
            frames = frames extraction(video file path)
            # Check if the extracted frames are equal to the SEQUENCE_LENGTH specified above.
            # So ignore the vides having frames less than the SEQUENCE LENGTH.
            if len(frames) == SEQUENCE_LENGTH:
                # Append the data to their repective lists.
                features.append(frames)
                labels.append(class_index)
```

```
video files paths.append(video file path)
   # Converting the list to numpy arrays
   features = np.asarray(features)
   labels = np.array(labels)
   # Return the frames, class index, and video file path.
   return features, labels, video_files_paths
# Create the dataset.
features, labels, video files paths = create dataset()
    Extracting Data of Class: WalkingWithDog
    Extracting Data of Class: TaiChi
    Extracting Data of Class: Swing
    Extracting Data of Class: HorseRace
1
2
# Using Keras's to_categorical method to convert labels into one-hot-encoded vectors
one hot encoded labels = to categorical(labels)
def create convlstm model():
   This function will construct the required convlstm model.
   Returns:
       model: It is the required constructed convlstm model.
   # We will use a Sequential model for model construction
   model = Sequential()
   # Define the Model Architecture.
   model.add(ConvLSTM2D(filters = 4, kernel_size = (3, 3), activation = 'tanh',data_format =
                       recurrent dropout=0.2, return sequences=True, input shape = (SEQUENC
                                                                                 IMAGE H
   model.add(MaxPooling3D(pool_size=(1, 2, 2), padding='same', data_format='channels_last'))
   model.add(TimeDistributed(Dropout(0.2)))
   model.add(ConvLSTM2D(filters = 8, kernel_size = (3, 3), activation = 'tanh', data_format
                       recurrent dropout=0.2, return sequences=True))
   model.add(MaxPooling3D(pool_size=(1, 2, 2), padding='same', data_format='channels_last'))
   model.add(TimeDistributed(Dropout(0.2)))
```

```
model.add(ConvLSTM2D(filters = 14, kernel_size = (3, 3), activation = 'tanh', data_format
                      recurrent_dropout=0.2, return_sequences=True))
   model.add(MaxPooling3D(pool_size=(1, 2, 2), padding='same', data_format='channels_last'))
   model.add(TimeDistributed(Dropout(0.2)))
   model.add(ConvLSTM2D(filters = 16, kernel_size = (3, 3), activation = 'tanh', data_format
                      recurrent dropout=0.2, return sequences=True))
   model.add(MaxPooling3D(pool_size=(1, 2, 2), padding='same', data_format='channels_last'))
   #model.add(TimeDistributed(Dropout(0.2)))
   model.add(Flatten())
   model.add(Dense(len(CLASSES LIST), activation = "softmax"))
   # Display the models summary.
   model.summary()
   # Return the constructed convlstm model.
   return model
# Construct the required convlstm model.
convlstm_model = create_convlstm_model()
# Display the success message.
print("Model Created Successfully!")
    Model: "sequential"
     Layer (type)
                            Output Shape
                                                     Param #
    ______
     conv_lstm2d (ConvLSTM2D) (None, 20, 62, 62, 4)
                                                     1024
     max pooling3d (MaxPooling3D (None, 20, 31, 31, 4)
     time distributed (TimeDistr (None, 20, 31, 31, 4)
     ibuted)
     conv_lstm2d_1 (ConvLSTM2D) (None, 20, 29, 29, 8)
                                                     3488
     max pooling3d 1 (MaxPooling (None, 20, 15, 15, 8)
     3D)
```

11144

time_distributed_1 (TimeDis (None, 20, 15, 15, 8)

conv lstm2d 2 (ConvLSTM2D) (None, 20, 13, 13, 14)

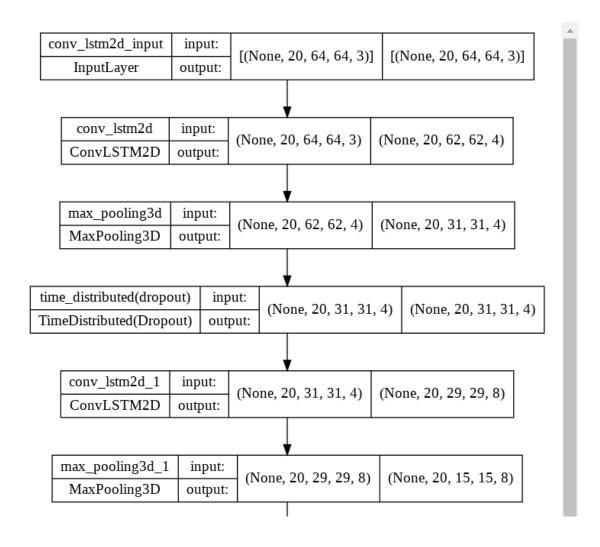
tributed)

```
max_pooling3d_2 (MaxPooling (None, 20, 7, 7, 14)
                                              0
3D)
time_distributed_2 (TimeDis (None, 20, 7, 7, 14)
tributed)
conv_lstm2d_3 (ConvLSTM2D) (None, 20, 5, 5, 16)
                                              17344
max_pooling3d_3 (MaxPooling (None, 20, 3, 3, 16)
                                              0
3D)
flatten (Flatten)
                        (None, 2880)
                                              0
dense (Dense)
                        (None, 4)
                                              11524
______
```

Total params: 44,524 Trainable params: 44,524 Non-trainable params: 0

Model Created Successfully!

Plot the structure of the contructed model. plot_model(convlstm_model, to_file = 'convlstm_model_structure_plot.png', show_shapes = True,



```
1
# Split the Data into Train ( 75% ) and Test Set ( 25% ).
features_train, features_test, labels_train, labels_test = train_test_split(features, one_hot_
         # Create an Instance of Early Stopping Callback
early_stopping_callback = EarlyStopping(monitor = 'val_loss', patience = 10, mode = 'min', re
# Compile the model and specify loss function, optimizer and metrics values to the model
convlstm_model.compile(loss = 'categorical_crossentropy', optimizer = 'Adam', metrics = ["acc
# Start training the model.
convlstm model training history = convlstm model.fit(x = features train, y = labels train, ep
    Epoch 1/50
    73/73 [============= ] - 148s 2s/step - loss: 1.3874 - accuracy: 0.2979
    Epoch 2/50
    73/73 [============= ] - 138s 2s/step - loss: 1.3407 - accuracy: 0.3322
    Epoch 3/50
    73/73 [============= ] - 139s 2s/step - loss: 1.2268 - accuracy: 0.4760
    Epoch 4/50
    73/73 [============== ] - 139s 2s/step - loss: 0.9917 - accuracy: 0.6096
    Epoch 5/50
```

```
73/73 [============ ] - 139s 2s/step - loss: 0.7571 - accuracy: 0.6918
Epoch 6/50
73/73 [=========== ] - 139s 2s/step - loss: 0.6136 - accuracy: 0.7534
Epoch 7/50
73/73 [============== ] - 139s 2s/step - loss: 0.5121 - accuracy: 0.7979
Epoch 8/50
73/73 [============ ] - 139s 2s/step - loss: 0.3390 - accuracy: 0.8699
Epoch 9/50
73/73 [============ ] - 140s 2s/step - loss: 0.2729 - accuracy: 0.9007
Epoch 10/50
73/73 [============= ] - 138s 2s/step - loss: 0.2915 - accuracy: 0.8801
Epoch 11/50
73/73 [============== ] - 138s 2s/step - loss: 0.2309 - accuracy: 0.9041
Epoch 12/50
73/73 [============ ] - 139s 2s/step - loss: 0.0646 - accuracy: 0.9863
Epoch 13/50
73/73 [=========== ] - 139s 2s/step - loss: 0.0747 - accuracy: 0.9760
Epoch 14/50
73/73 [============== ] - 139s 2s/step - loss: 0.0812 - accuracy: 0.9692
Epoch 15/50
Epoch 16/50
73/73 [============ ] - 139s 2s/step - loss: 0.0914 - accuracy: 0.9658
Epoch 17/50
73/73 [============ ] - 139s 2s/step - loss: 0.0479 - accuracy: 0.9897
Epoch 18/50
Epoch 19/50
73/73 [============= ] - 139s 2s/step - loss: 0.0228 - accuracy: 0.9966
Epoch 20/50
73/73 [============ ] - 138s 2s/step - loss: 0.1182 - accuracy: 0.9623
Epoch 21/50
73/73 [=========== ] - 138s 2s/step - loss: 0.0846 - accuracy: 0.9795
Epoch 22/50
Epoch 23/50
73/73 [============ ] - 138s 2s/step - loss: 0.0284 - accuracy: 0.9897
```

- # Get the loss and accuracy from model_evaluation_history.
 model_evaluation_loss, model_evaluation_accuracy = model_evaluation_history
- # Define the string date format.
- # Get the current Date and Time in a DateTime Object.
- # Convert the DateTime object to string according to the style mentioned in date_time_format

```
date time format = '%Y %m %d %H %M %S'
current date time dt = dt.datetime.now()
current_date_time_string = dt.datetime.strftime(current_date_time_dt, date_time_format)
# Define a useful name for our model to make it easy for us while navigating through multiple
model file name = f'convlstm model Date Time {current date time string} Loss {model evalu
# Save your Model.
convlstm model.save(model file name)
1
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27
def plot_metric(model_training_history, metric_name_1, metric_name_2, plot_name):
   This function will plot the metrics passed to it in a graph.
   Args:
       model training history: A history object containing a record of training and validati
                                loss values and metrics values at successive epochs
       metric_name_1:
                                The name of the first metric that needs to be plotted in the
       metric_name_2:
                                The name of the second metric that needs to be plotted in the
       plot_name:
                                The title of the graph.
   # Get metric values using metric names as identifiers.
   metric_value_1 = model_training_history.history[metric_name_1]
```

```
metric_value_2 = model_training_history.history[metric_name_2]

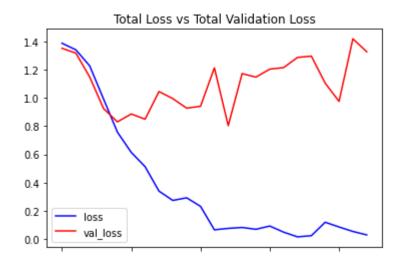
# Construct a range object which will be used as x-axis (horizontal plane) of the graph.
epochs = range(len(metric_value_1))

# Plot the Graph.
plt.plot(epochs, metric_value_1, 'blue', label = metric_name_1)
plt.plot(epochs, metric_value_2, 'red', label = metric_name_2)

# Add title to the plot.
plt.title(str(plot_name))

# Add legend to the plot.
plt.legend()
```

Visualize the training and validation loss metrices.
plot_metric(convlstm_model_training_history, 'loss', 'val_loss', 'Total Loss vs Total Validat



Visualize the training and validation accuracy metrices.
plot_metric(convlstm_model_training_history, 'accuracy', 'val_accuracy', 'Total Accuracy vs T

Total Accuracy vs Total Validation Accuracy 1.0 accuracy val_accuracy 0.9

```
def create LRCN model():
   This function will construct the required LRCN model.
   Returns:
       model: It is the required constructed LRCN model.
   # We will use a Sequential model for model construction.
   model = Sequential()
   # Define the Model Architecture.
   model.add(TimeDistributed(Conv2D(16, (3, 3), padding='same',activation = 'relu'),
                          input_shape = (SEQUENCE_LENGTH, IMAGE_HEIGHT, IMAGE_WIDTH, 3)))
   model.add(TimeDistributed(MaxPooling2D((4, 4))))
   model.add(TimeDistributed(Dropout(0.25)))
   model.add(TimeDistributed(Conv2D(32, (3, 3), padding='same',activation = 'relu')))
   model.add(TimeDistributed(MaxPooling2D((4, 4))))
   model.add(TimeDistributed(Dropout(0.25)))
   model.add(TimeDistributed(Conv2D(64, (3, 3), padding='same',activation = 'relu')))
   model.add(TimeDistributed(MaxPooling2D((2, 2))))
   model.add(TimeDistributed(Dropout(0.25)))
   model.add(TimeDistributed(Conv2D(64, (3, 3), padding='same',activation = 'relu')))
   model.add(TimeDistributed(MaxPooling2D((2, 2))))
   #model.add(TimeDistributed(Dropout(0.25)))
   model.add(TimeDistributed(Flatten()))
   model.add(LSTM(32))
   model.add(Dense(len(CLASSES LIST), activation = 'softmax'))
   # Display the models summary.
   model.summary()
   # Return the constructed LRCN model.
   return model
# Construct the required LRCN model.
LRCN_model = create_LRCN_model()
# Display the success message.
print("Model Created Successfully!")
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
time_distributed_3 (TimeDistributed)		
<pre>time_distributed_4 (TimeDis tributed)</pre>	(None, 20, 16, 16, 16)	0
<pre>time_distributed_5 (TimeDis tributed)</pre>	(None, 20, 16, 16, 16)	0
<pre>time_distributed_6 (TimeDis tributed)</pre>	(None, 20, 16, 16, 32)	4640
<pre>time_distributed_7 (TimeDis tributed)</pre>	(None, 20, 4, 4, 32)	0
<pre>time_distributed_8 (TimeDis tributed)</pre>	(None, 20, 4, 4, 32)	0
<pre>time_distributed_9 (TimeDis tributed)</pre>	(None, 20, 4, 4, 64)	18496
<pre>time_distributed_10 (TimeDi stributed)</pre>	(None, 20, 2, 2, 64)	0
<pre>time_distributed_11 (TimeDi stributed)</pre>	(None, 20, 2, 2, 64)	0
<pre>time_distributed_12 (TimeDi stributed)</pre>	(None, 20, 2, 2, 64)	36928
<pre>time_distributed_13 (TimeDi stributed)</pre>	(None, 20, 1, 1, 64)	0
<pre>time_distributed_14 (TimeDi stributed)</pre>	(None, 20, 64)	0
lstm (LSTM)	(None, 32)	12416
dense_1 (Dense)	(None, 4)	132

Total params: 73,060 Trainable params: 73,060 Non-trainable params: 0

Model Created Successfully!

Plot the structure of the contructed LRCN model.
plot_model(LRCN_model, to_file = 'LRCN_model_structure_plot.png', show_shapes = True, show_la

time_distributed_3_input	input:	[(None, 20, 64, 64, 3)]		[(None 20 64 64 2)]
InputLayer	output:			[(None, 20, 64, 64, 3)]

```
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# Create an Instance of Early Stopping Callback.
early_stopping_callback = EarlyStopping(monitor = 'val_loss', patience = 15, mode = 'min', re
# Compile the model and specify loss function, optimizer and metrics to the model.
LRCN_model.compile(loss = 'categorical_crossentropy', optimizer = 'Adam', metrics = ["accurac
# Start training the model.
LRCN_model_training_history = LRCN_model.fit(x = features_train, y = labels_train, epochs = 5
   Epoch 1/50
   Epoch 2/50
   Epoch 3/50
   73/73 [============ ] - 13s 178ms/step - loss: 1.2244 - accuracy: 0.45!
   Epoch 4/50
   73/73 [============= ] - 13s 178ms/step - loss: 1.1435 - accuracy: 0.516
   Epoch 5/50
   73/73 [============= ] - 13s 179ms/step - loss: 1.0011 - accuracy: 0.602
   Epoch 6/50
   73/73 [============= ] - 13s 178ms/step - loss: 0.9180 - accuracy: 0.616
   Epoch 7/50
   73/73 [============ ] - 13s 178ms/step - loss: 0.9012 - accuracy: 0.616
   Epoch 8/50
   Epoch 9/50
   73/73 [============= ] - 13s 178ms/step - loss: 0.7579 - accuracy: 0.688
   Epoch 10/50
   73/73 [============= ] - 13s 178ms/step - loss: 0.6774 - accuracy: 0.732
   Epoch 11/50
   73/73 [============= ] - 13s 177ms/step - loss: 0.5738 - accuracy: 0.787
   Epoch 12/50
   73/73 [=================== ] - 13s 178ms/step - loss: 0.5762 - accuracy: 0.791
   Epoch 13/50
   73/73 [============ ] - 13s 176ms/step - loss: 0.5474 - accuracy: 0.791
   Epoch 14/50
   73/73 [============= ] - 13s 177ms/step - loss: 0.3842 - accuracy: 0.87
   Epoch 15/50
   73/73 [================== ] - 13s 177ms/step - loss: 0.3665 - accuracy: 0.869
   Epoch 16/50
```

```
Epoch 17/50
    73/73 [=========== ] - 13s 178ms/step - loss: 0.2634 - accuracy: 0.907
    Epoch 18/50
    Epoch 19/50
    73/73 [============= ] - 13s 178ms/step - loss: 0.2178 - accuracy: 0.938
    Epoch 20/50
    73/73 [============ ] - 13s 178ms/step - loss: 0.3693 - accuracy: 0.886
    Epoch 21/50
    73/73 [=========== ] - 13s 178ms/step - loss: 0.1706 - accuracy: 0.948
    Epoch 22/50
    55/73 [=========>.....] - ETA: 2s - loss: 0.2385 - accuracy: 0.9227
# Evaluate the trained model.
model evaluation history = LRCN model.evaluate(features test, labels test)
# Get the loss and accuracy from model_evaluation_history.
model evaluation loss, model evaluation accuracy = model evaluation history
# Define the string date format.
# Get the current Date and Time in a DateTime Object.
# Convert the DateTime object to string according to the style mentioned in date_time_format
date time format = '%Y %m %d %H %M %S'
current_date_time_dt = dt.datetime.now()
current_date_time_string = dt.datetime.strftime(current_date_time_dt, date_time_format)
# Define a useful name for our model to make it easy for us while navigating through multiple
model file name = f'LRCN model Date Time {current date time string} Loss {model evaluatio
```

73/73 [=============] - 13s 177ms/step - loss: 0.3413 - accuracy: 0.887

```
# Save the Model.
LRCN_model.save(model_file_name)
1
2
# Visualize the training and validation loss metrices.
plot_metric(LRCN_model_training_history, 'loss', 'val_loss', 'Total Loss vs Total Validation
1
2
# Visualize the training and validation accuracy metrices.
plot_metric(LRCN_model_training_history, 'accuracy', 'val_accuracy', 'Total Accuracy vs Total
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def download_youtube_videos(youtube_video_url, output_directory):
    This function downloads the youtube video whose URL is passed to it as an argument.
    Args:
        youtube_video_url: URL of the video that is required to be downloaded.
        output_directory: The directory path to which the video needs to be stored after dow
```

```
Returns:
       title: The title of the downloaded youtube video.
    # Create a video object which contains useful information about the video.
     video = pafy.new(youtube video url)
     # Retrieve the title of the video.
     title = video.title
     # Get the best available quality object for the video.
     video_best = video.getbest()
     # Construct the output file path.
     output_file_path = f'{output_directory}/{title}.mp4'
     # Download the youtube video at the best available quality and store it to the contructe
     video_best.download(filepath = output_file_path, quiet = True)
     # Return the video title.
     return title
!pip install git+https://github.com/Cupcakus/pafy
!pip uninstall -y pafy
!pip install git+https://github.com/Cupcakus/pafy
# Make the Output directory if it does not exist
test videos directory = 'test videos'
os.makedirs(test_videos_directory, exist_ok = True)
# Download a YouTube Video.
video title = download youtube videos('https://www.youtube.com/watch?v=8u0qjmHIOcE', test vid
# Get the YouTube Video's path we just downloaded.
input_video_file_path = f'{test_videos_directory}/{video_title}.mp4'
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def predict_on_video(video_file_path, output_file_path, SEQUENCE_LENGTH):
   This function will perform action recognition on a video using the LRCN model.
   Args:
   video file path: The path of the video stored in the disk on which the action recognitio
   output_file_path: The path where the ouput video with the predicted action being performe
   SEQUENCE_LENGTH: The fixed number of frames of a video that can be passed to the model a
   # Initialize the VideoCapture object to read from the video file.
   video_reader = cv2.VideoCapture(video_file_path)
   # Get the width and height of the video.
   original_video_width = int(video_reader.get(cv2.CAP_PROP_FRAME_WIDTH))
   original video height = int(video reader.get(cv2.CAP PROP FRAME HEIGHT))
   # Initialize the VideoWriter Object to store the output video in the disk.
   video_writer = cv2.VideoWriter(output_file_path, cv2.VideoWriter_fourcc('M', 'P', '4', 'V
                                   video_reader.get(cv2.CAP_PROP_FPS), (original_video_width,
   # Declare a queue to store video frames.
   frames queue = deque(maxlen = SEQUENCE LENGTH)
   # Initialize a variable to store the predicted action being performed in the video.
   predicted class name = ''
   # Iterate until the video is accessed successfully.
   while video_reader.isOpened():
        # Read the frame.
       ok, frame = video_reader.read()
        # Check if frame is not read properly then break the loop.
        if not ok:
            break
```

```
# Resize the Frame to fixed Dimensions.
        resized_frame = cv2.resize(frame, (IMAGE_HEIGHT, IMAGE_WIDTH))
        # Normalize the resized frame by dividing it with 255 so that each pixel value then 1
        normalized frame = resized frame / 255
        # Appending the pre-processed frame into the frames list.
        frames queue.append(normalized frame)
       # Check if the number of frames in the queue are equal to the fixed sequence length.
        if len(frames_queue) == SEQUENCE_LENGTH:
            # Pass the normalized frames to the model and get the predicted probabilities.
            predicted_labels_probabilities = LRCN_model.predict(np.expand_dims(frames_queue,
            # Get the index of class with highest probability.
            predicted_label = np.argmax(predicted_labels_probabilities)
            # Get the class name using the retrieved index.
            predicted_class_name = CLASSES_LIST[predicted_label]
        # Write predicted class name on top of the frame.
        cv2.putText(frame, predicted class name, (10, 30), cv2.FONT HERSHEY SIMPLEX, 1, (0, 2
        # Write The frame into the disk using the VideoWriter Object.
        video_writer.write(frame)
   # Release the VideoCapture and VideoWriter objects.
   video reader.release()
   video writer.release()
# Construct the output video path.
output_video_file_path = f'{test_videos_directory}/{video_title}-Output-SeqLen{SEQUENCE_LENGT
# Perform Action Recognition on the Test Video.
predict_on_video(input_video_file_path, output_video_file_path, SEQUENCE_LENGTH)
# Display the output video.
VideoFileClip(output_video_file_path, audio=False, target_resolution=(300,None)).ipython_disp
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def predict single action(video file path, SEQUENCE LENGTH):
   This function will perform single action recognition prediction on a video using the LRCN
   Args:
   video file path: The path of the video stored in the disk on which the action recognitio
   SEQUENCE LENGTH: The fixed number of frames of a video that can be passed to the model a
   # Initialize the VideoCapture object to read from the video file.
   video reader = cv2.VideoCapture(video file path)
   # Get the width and height of the video.
   original video width = int(video reader.get(cv2.CAP PROP FRAME WIDTH))
   original_video_height = int(video_reader.get(cv2.CAP_PROP_FRAME_HEIGHT))
   # Declare a list to store video frames we will extract.
   frames_list = []
   # Initialize a variable to store the predicted action being performed in the video.
   predicted class name = ''
   # Get the number of frames in the video.
   video frames count = int(video reader.get(cv2.CAP PROP FRAME COUNT))
   # Calculate the interval after which frames will be added to the list.
    skip_frames_window = max(int(video_frames_count/SEQUENCE_LENGTH),1)
   # Iterating the number of times equal to the fixed length of sequence.
   for frame_counter in range(SEQUENCE_LENGTH):
        # Set the current frame position of the video.
       video_reader.set(cv2.CAP_PROP_POS_FRAMES, frame_counter * skip_frames_window)
        # Read a frame.
        success, frame = video reader.read()
        # Check if frame is not read properly then break the loop.
        if not success:
```

```
# Resize the Frame to fixed Dimensions.
        resized frame = cv2.resize(frame, (IMAGE HEIGHT, IMAGE WIDTH))
        \# Normalize the resized frame by dividing it with 255 so that each pixel value then 1
        normalized frame = resized frame / 255
        # Appending the pre-processed frame into the frames list
       frames_list.append(normalized_frame)
   # Passing the pre-processed frames to the model and get the predicted probabilities.
   predicted_labels_probabilities = convlstm_model.predict(np.expand_dims(frames_list, axis
   # Get the index of class with highest probability.
   predicted label = np.argmax(predicted labels probabilities)
   # Get the class name using the retrieved index.
   predicted class name = CLASSES LIST[predicted label]
   # Display the predicted action along with the prediction confidence.
   print(f'Action Predicted: {predicted_class_name}\nConfidence: {predicted_labels_probabili
   # Release the VideoCapture object.
   video_reader.release()
# Download the youtube video.
video_title = download_youtube_videos('https://www.youtube.com/watch?v=XqqpZS0c1K0', test_vid
# Construct tihe nput youtube video path
input_video_file_path = f'{test_videos_directory}/{video_title}.mp4'
# Perform Single Prediction on the Test Video.
predict_single_action(input_video_file_path, SEQUENCE_LENGTH)
# Display the input video.
VideoFileClip(input_video_file_path, audio=False, target_resolution=(300,None)).ipython_displ
```