```
\mbox{\tt\#} Discards the output of the cell
# To work with youtube videos
!pip install pafy youtube-dl moviepy
# libraries
import os
import cv2
import pafy
import math
import random
\hbox{import numpy as np}\\
import pandas as pd
import\ {\tt matplotlib.pyplot}\ as\ {\tt plt}
from collections import deque
from moviepy.editor import \mbox{*}
%matplotlib inline
from sklearn.model_selection import train_test_split
import tensorflow as tf
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
\# set Numpy, Python and Tensorflow seeds to get consistent results on every execution
# restricting the randomness
seed_constant = 27
np.random.seed(seed_constant)
random.seed(seed_constant)
{\tt tf.random.set\_seed(seed\_constant)}
\mbox{\tt\#} Discards the output of the cell
%%capture
\# Downloading the UCF50 Action dataset from the web
!wget --no-check-certificate https://www.crcv.ucf.edu/data/UCF50.rar
# Extract the dataset
!unrar x UCF50.rar
```

## Visualizing the dataset

```
# create and specify size of matplot figure
plt.figure(figsize = (20, 20))
# get names of all action categories
all_classes_names = os.listdir('UCF50')
# get 20 random categories
random_range = random.sample(range(len(all_classes_names)), 20)
\ensuremath{\text{\#}} iterate through all the generated random values
for counter, random_index in enumerate(random_range, 1):
    \ensuremath{\text{\#}} get the name of the random category
    selected_class_Name = all_classes_names[random_index]
    \# get the list of all the video files present in selected_class_Name
    video_files_names_list = os.listdir(f'UCF50/{selected_class_Name}')
    # randomly select a video file from the list
    selected_video_file_name = random.choice(video_files_names_list)
    # video capture object to read 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 video capture object
    video_reader.release()
    \mbox{\tt\#} convert the frame from BGR into RGB format
    rgb_frame = cv2.cvtColor(bgr_frame, cv2.COLOR_BGR2RGB)
    \mbox{\tt\#} write the class name on the video frame (USED TO WRITE ON THE VIDEO)
    cv2.putText(rgb_frame, selected_class_Name, (10, 30), cv2.FONT_HERSHEY_SIMPLEX, 1, (255, 0, 0), 2)
    # display the frame
    plt.subplot(5, 4, counter)
    plt.imshow(rgb_frame)
    plt.axis('off')
```









































```
from re import I
# resizing the video frames in our dataset
img_height, img_width = 64, 64

# specify the number of frames of a video that will be fed to the model as one sequence
sequence_length = 20

# specifying the dataset directory
dataset_dir = "UCF50"

# Specifying the list of classes used for training the model
classes_list = ["PullUps", "BenchPress", "Punch", "PlayingGuitar", "PushUps"]
```

## Function to Extract, Resize and Normalize the frames

```
# function extracts the required frame from the video after resizing and normalizing it and then returns the a list of resized and norm
def frame_extraction(video_path):
 frames_list = []
  # reading the video file using the VideoCapture object
  video_reader = cv2.VideoCapture(video_path)
  # counting the total number of frames in the video file
  video_frames_count = int(video_reader.get(cv2.CAP_PROP_FRAME_COUNT))
  # calculating the interval after which frames will be added
  skip_frames_window = max(int(video_frames_count/sequence_length), 1)
  # iterate through the video frames
  for frame_counter in range(sequence_length):
    \ensuremath{\text{\#}} set the current frame position of the video
    video_reader.set(cv2.CAP_PROP_POS_FRAMES, frame_counter * skip_frames_window)
    # read a frame from the video
    success, frame = video_reader.read()
    # check if the frame is not successfully read
   if not success:
      break
    # resize the frame
    resized_frame = cv2.resize(frame, (img_height, img_width))
    # normalize the resized frame by dividing it with 255 so that each pixel value then lies between 0 and 1
    normalized_frame = resized_frame / 255
    # append the normalized frame into the frames list
    frames_list.append(normalized_frame)
  # release the video capture object
  video_reader.release()
  # return the frames list
  return frames_list
```

```
# Function for dataset creation
this function returns:
  features: a list containing extracted frames of videos
  labels: a list containing the corresponding labels of the extracted frames
 video_files_paths: a list containing the paths of the videos from which the frames were extracted
def create_dataset():
  features = []
  labels = []
  video_files_paths = []
  # iterating through all the classes mentioned in the class list
  for class_index, class_name in enumerate(classes_list):
    # Display name of the class
    print(f'Extracting data from class: {class_name}')
    # get the list of video files present in the class
    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 video file path
      video_file_path = os.path.join(dataset_dir, class_name, file_name)
      # extract the frames from the video file
      frames = frame_extraction(video_file_path)
      \# check if the extracted frames is equal to the sequence length i.e. 20
      # ignore videos having frames less than 20
      if len(frames) == sequence_length:
        # append the data
        features.append(frames)
        labels.append(class_index)
        video_files_paths.append(video_file_path)
  # convert the features and labels lists to numpy arrays
  features = np.asarray(features)
  labels = np.array(labels)
  # return the features, labels and video files paths
  return features, labels, video_files_paths
```

### creating the required dataset

# Long-term Reccurence Convolutional Network Model

```
def create_LRCN_model():
 model = Sequential()
  model.add(TimeDistributed(Conv2D(16, (3, 3), padding = 'same', activation = 'relu'), input_shape = (sequence_length, img_height, img_
  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'))
  model.summary()
  return model
```

```
# Constructing model
LRCN_model = create_LRCN_model()
print("Model Created Successfully")
```

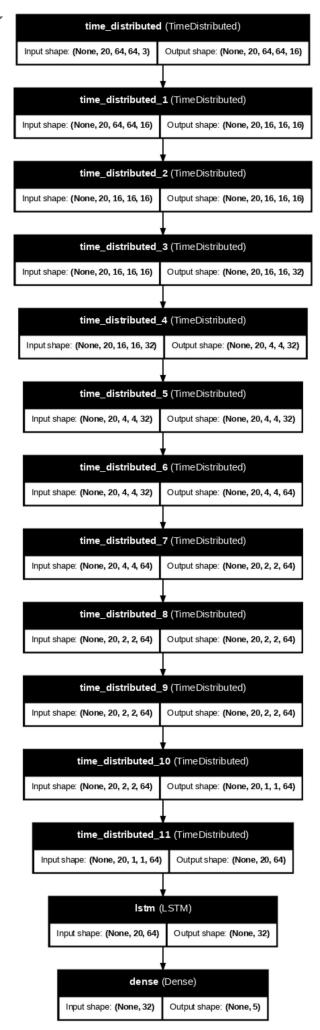
 $\overline{\mathcal{F}}$ 

on3.10/dist-packages/keras/src/layers/core/wrapper.py:27: UserWarning: Do not pass an `input\_shape`/`input\_dim` ; \*\*kwargs)

	Output Shape	Param #
(TimeDistributed)	(None, 20, 64, 64, 16)	448
1 (TimeDistributed)	(None, 20, 16, 16, 16)	0
2 (TimeDistributed)	(None, 20, 16, 16, 16)	0
3 (TimeDistributed)	(None, 20, 16, 16, 32)	4,640
4 (TimeDistributed)	(None, 20, 4, 4, 32)	0
5 (TimeDistributed)	(None, 20, 4, 4, 32)	0
6 (TimeDistributed)	(None, 20, 4, 4, 64)	18,496
7 (TimeDistributed)	(None, 20, 2, 2, 64)	0
8 (TimeDistributed)	(None, 20, 2, 2, 64)	0
9 (TimeDistributed)	(None, 20, 2, 2, 64)	36,928
10	(None, 20, 1, 1, 64)	0
11	(None, 20, 64)	0
	(None, 32)	12,416
	(None, 5)	165

```
93 (285.52 KB)
73,093 (285.52 KB)
ms: 0 (0.00 B)
ssfully
```

```
# Plotting the structure of the model
plot_model(LRCN_model, to_file = 'LRCN_model.png', show_shapes = True, show_layer_names = True, dpi = 66)
```



## Compiling and Training the model

```
#Compiling and Training
early_stopping_callback = EarlyStopping(monitor = 'val_loss', patience = 15, mode = 'min', restore_best_weights = True)
LRCN_model.compile(loss = 'categorical_crossentropy', optimizer = 'Adam', metrics = ["accuracy"])
LRCN_model_training_history = LRCN_model.fit(x = features_train, y = labels_train, epochs = 50, batch_size = 4, shuffle = True, validat
    Epoch 13/50
₹
                                 - 52s 493ms/step - accuracy: 0.8636 - loss: 0.4060 - val_accuracy: 0.7642 - val_loss: 0.4879
     106/106
     Epoch 14/50
     106/106
                                 84s 514ms/step - accuracy: 0.8825 - loss: 0.3471 - val_accuracy: 0.8019 - val_loss: 0.5516
     Epoch 15/50
     106/106
                                  84s 541ms/step - accuracy: 0.8638 - loss: 0.3950 - val_accuracy: 0.8774 - val_loss: 0.3922
     Epoch 16/50
     106/106
                                  80s 525ms/step - accuracy: 0.9446 - loss: 0.1640 - val_accuracy: 0.8585 - val_loss: 0.3572
     Epoch 17/50
                                 86s 565ms/step - accuracy: 0.9610 - loss: 0.1479 - val_accuracy: 0.8868 - val_loss: 0.2767
     106/106
     Epoch 18/50
                                 - 87s 616ms/step - accuracy: 0.9703 - loss: 0.1265 - val_accuracy: 0.9528 - val_loss: 0.1804
     106/106
     Epoch 19/50
     106/106
                                 - 71s 514ms/step - accuracy: 0.9606 - loss: 0.1376 - val_accuracy: 0.9434 - val_loss: 0.2132
     Epoch 20/50
     106/106
                                 97s 658ms/step - accuracy: 0.9800 - loss: 0.0973 - val_accuracy: 0.7547 - val_loss: 0.7290
     Epoch 21/50
     106/106
                                 69s 535ms/step - accuracy: 0.9061 - loss: 0.2602 - val_accuracy: 0.8585 - val_loss: 0.3987
     Epoch 22/50
     106/106
                                 - 78s 496ms/step - accuracy: 0.9617 - loss: 0.1047 - val accuracy: 0.9245 - val loss: 0.2539
     Epoch 23/50
     106/106
                                 - 86s 529ms/step - accuracy: 0.9890 - loss: 0.0582 - val accuracy: 0.9245 - val loss: 0.2439
     Epoch 24/50
     106/106
                                 54s 511ms/step - accuracy: 0.9879 - loss: 0.0680 - val_accuracy: 0.8396 - val_loss: 0.5938
     Epoch 25/50
     106/106
                                 86s 551ms/step - accuracy: 0.9347 - loss: 0.1752 - val_accuracy: 0.8868 - val_loss: 0.3083
     Epoch 26/50
     106/106
                                 82s 553ms/step - accuracy: 0.9530 - loss: 0.1842 - val_accuracy: 0.9811 - val_loss: 0.1021
     Epoch 27/50
     106/106
                                  60s 567ms/step - accuracy: 0.9915 - loss: 0.0339 - val_accuracy: 0.9623 - val_loss: 0.1754
     Epoch 28/50
     106/106
                                 - 80s 546ms/step - accuracy: 0.9424 - loss: 0.1720 - val accuracy: 0.9340 - val loss: 0.2635
     Epoch 29/50
     106/106
                                 83s 556ms/step - accuracy: 0.9758 - loss: 0.0897 - val_accuracy: 0.9623 - val_loss: 0.1439
     Epoch 30/50
     106/106
                                 75s 485ms/step - accuracy: 1.0000 - loss: 0.0112 - val_accuracy: 0.9717 - val_loss: 0.1261
     Epoch 31/50
                                 82s 489ms/step - accuracy: 1.0000 - loss: 0.0077 - val_accuracy: 0.9717 - val_loss: 0.1321
     106/106
     Epoch 32/50
     106/106
                                 58s 548ms/step - accuracy: 1.0000 - loss: 0.0064 - val_accuracy: 0.9717 - val_loss: 0.1376
     Epoch 33/50
     106/106
                                 - 94s 665ms/step - accuracy: 1.0000 - loss: 0.0052 - val accuracy: 0.9717 - val loss: 0.1387
     Epoch 34/50
     106/106
                                 - 64s 603ms/step - accuracy: 1.0000 - loss: 0.0045 - val_accuracy: 0.9717 - val_loss: 0.1410
     Epoch 35/50
     106/106
                                 - 80s 588ms/step - accuracy: 1.0000 - loss: 0.0042 - val_accuracy: 0.9717 - val_loss: 0.1442
     Epoch 36/50
     106/106
                                  80s 573ms/step - accuracy: 1.0000 - loss: 0.0035 - val_accuracy: 0.9717 - val_loss: 0.1410
     Epoch 37/50
     106/106
                                 58s 552ms/step - accuracy: 1.0000 - loss: 0.0031 - val accuracy: 0.9717 - val loss: 0.1429
     Epoch 38/50
     106/106
                                 - 79s 520ms/step - accuracy: 1.0000 - loss: 0.0028 - val_accuracy: 0.9717 - val_loss: 0.1441
     Epoch 39/50
     106/106
                                 87s 561ms/step - accuracy: 1.0000 - loss: 0.0025 - val_accuracy: 0.9717 - val_loss: 0.1446
     Epoch 40/50
     106/106
                                 - 81s 560ms/step - accuracy: 1.0000 - loss: 0.0023 - val_accuracy: 0.9717 - val_loss: 0.1471
     Epoch 41/50
     106/106
                                 - 85s 581ms/step - accuracy: 1.0000 - loss: 0.0020 - val_accuracy: 0.9717 - val_loss: 0.1487
```

### Evaluating the trained model

```
model_evaluation_history = LRCN_model.evaluate(features_test, labels_test)

$\frac{1}{2}$ 6/6 3s 470ms/step - accuracy: 0.9381 - loss: 0.2794

# saving the model
LRCN_model.save('LRCN_Human_Activity_Recognition_System.h5')
```

⇒ WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save\_model(model)`. This file format is

# Model Accuracy and Loss Curves

```
def plot_metric(model_training_history, metric_name1, metric_name2, plot_name):
    metric_value1 = model_training_history.history[metric_name1]
    metric_value2 = model_training_history.history[metric_name2]

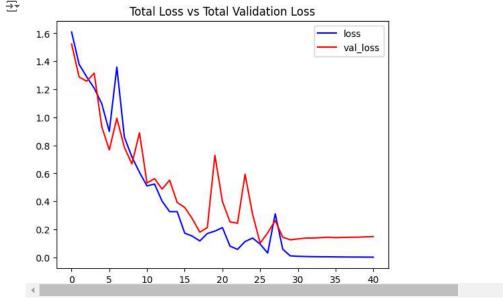
epochs = range(len(metric_value1))

plt.plot(epochs, metric_value1, 'blue', label = metric_name1)
    plt.plot(epochs, metric_value2, 'red', label = metric_name2)

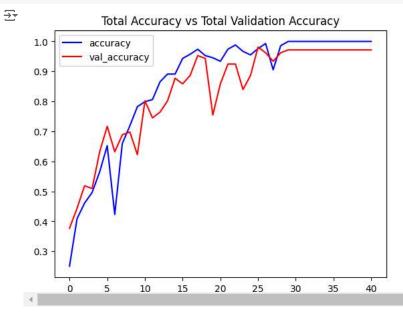
plt.title(str(plot_name))
    plt.legend()
    plt.show()

# Graph for Total Loss vs Validation Loss
plot_metric(LRCN_model_training_history, 'loss', 'val_loss', 'Total Loss vs Total Validation Loss')

Total Loss vs Total Validation Loss
```



# Graph for Total Accuracy vs Validation Accuracy plot\_metric(LRCN\_model\_training\_history, 'accuracy', 'val\_accuracy', 'Total Accuracy vs Total Validation Accuracy')



Implementing functions to deal with youtube videos

```
The function downloads the youtube video whose URL is passed to it as an argument.
        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 downloading.
    It returns the title of the downloaded youtube video.
{\tt def\ download\_youtube\_videos(youtube\_video\_url,\ output\_directory):}
  import youtube_dl
  # Create a video object which contains useful information about the video.
  ydl_opts = {'quiet': True, 'verbose': True} # Add verbose flag
  with youtube_dl.YoutubeDL(ydl_opts) as ydl:
    info_dict = ydl.extract_info(youtube_video_url, download=False)
    video_title = info_dict.get('title', None)
     # Create a video object which contains useful information about the video.
  video = pafy.new(youtube_video_url)
  # Get the best available quality object for the video.
  video_best = video.getbest()
  # Construct the output file path.
  output_file_path = f'{output_directory}/{video_title}.mp4'
# Make the output directory if it does not exist
test_videos_directory = 'test_videos'
os.makedirs(test_videos_directory, exist_ok = True)
  Leralli Atdeo_ctrte
# downloading a video
\label{eq:video_title} video = download\_youtube\_videos('https://www.youtube.com/watch?v=8u0qjmHIOcE', test\_videos\_directory) \\
\ensuremath{\text{\# Get}} the YouTube Video's path we just downloaded.
input_video_file_path = f'{test_videos_directory}/{video_title}.mp4'
```