```
In [ ]:
    #!pip install wandb
    #import wandb
    #wandb.init()
In ...
    #Importing Modules
    #Importing Keras and import sub-modules needed
    import keras
    from keras import applications
    from keras.preprocessing.image import ImageDataGenerator
    from keras import optimizers
    from keras.models import Sequential, Model
    from keras.layers import *
    from keras.callbacks import ModelCheckpoint, LearningRateScheduler, TensorBoard,
    #Importing miscallaneous modules
    import os
    import cv2
    import numpy as np
    from sklearn.model_selection import train_test_split
    import matplotlib.pyplot as plt
     #Importing sklearn modules to calculate different metrics and create different
    from sklearn.metrics import accuracy score
    from sklearn.metrics import precision_score
    from sklearn.metrics import recall score
    from sklearn.metrics import f1 score
    from sklearn.metrics import cohen_kappa_score
    from sklearn.metrics import roc auc score
    from sklearn.metrics import multilabel_confusion_matrix
    from tensorflow.keras.utils import to_categorical
I...
   from google.colab import drive
                                      #Access Google Drive which is used as location
   drive.mount('/gdrive')
   #go to root of Google Drive
   %cd /gdrive
Drive already mounted at /gdrive; to attempt to forcibly remount, call drive.mount
("/gdrive", force_remount=True).
/gdrive
In [ ]:
    #Navigate to folder where all the datasets are
    %cd 'My Drive'
    %cd 'Action Recognition'
/gdrive/My Drive
/gdrive/My Drive/Action Recognition
In...
   data_dir = "hmdb51/" #Choose dataset by naming dataset folder name
   img_height , img_width = 64, 64 #Set pixel values for frames
   seq_len = 70 #Set number of frames/samples per video
   classes = ["pullup", "punch", "dive", "fencing", "ride_bike", "golf"] #Select classes
l...
```

```
X, Y = create data(data dir)
                                                                                                                                                                                                                                         #Fetch data for
              #print (X.shape)
               #print (Y.shape)
['dribble', 'draw_sword', 'chew', 'dive', 'catch', 'climb_stairs', 'climb', 'clap', 'cartwheel', 'brush_hair', 'drink', 'fall_floor', 'jump', 'hug', 'eat', 'hit', 'flic_flac', 'handstand', 'golf', 'fencing', 'kick', 'kick_ball', 'kiss', 'punch', 'laug h', 'pick', 'pour', 'pushup', 'pullup', 'push', 'ride_horse', 'ride_bike', 'run', 's hake_hands', 'shoot_gun', 'somersault', 'situp', 'stand', 'shoot_bow', 'smoke', 'sit', 'shoot_ball', 'smile', 'walk', 'sword', 'throw', 'turn', 'swing_baseball', 'throw', 'turn', 'swing_baseball', 'throw', 'turn', 'throw', 'turn', 'throw', 't
d exercise', 'wave', 'talk']
pullup
Defected frame
Defected frame
Defected frame
punch
Defected frame
```

Defected frame

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.20, shuffle=
  print (X_train.shape)
  print (y_train.shape)
  print (X_test.shape)
  print (y_test.shape)
(344, 70, 64, 64, 3)
(344, 6)
(86, 70, 64, 64, 3)
(86, 6)
  model = Sequential() #Model initiated and layers added whilst specifying hyperpar
  model.add(ConvLSTM2D(filters = 64, kernel_size = (3, 3), return_sequences = False,
  model.add(Dropout(0.2))
  model.add(Conv2D(filters = 128, kernel size = (3, 3), activation = 'relu'))
  model.add(Dropout(0.2))
  model.add(Flatten())
  model.add(Dense(256, activation="relu"))
  model.add(Dense(256, activation="relu"))
  model.add(Dropout(0.3))
  model.add(Dense(6, activation = "softmax"))
  model.summary() #Print summary of model
  opt = keras.optimizers.SGD(lr=0.001)
                                           #Specify training algorithm and learning r
  model.compile(loss='categorical_crossentropy', optimizer=opt, metrics=["accuracy"]
```

Model: "sequential"

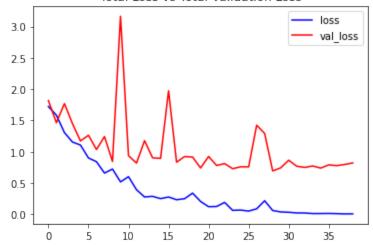
Layer (type)	Output Shape	Param #
conv_lst_m2d (ConvLSTM2D)	(None, 62, 62, 64)	154624
dropout (Dropout)	(None, 62, 62, 64)	0
conv2d (Conv2D)	(None, 60, 60, 128)	73856
dropout_1 (Dropout)	(None, 60, 60, 128)	0
flatten (Flatten)	(None, 460800)	0
dense (Dense)	(None, 256)	117965056
dense_1 (Dense)	(None, 256)	65792
dropout_2 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 6)	1542

Total params: 118,260,870 Trainable params: 118,260,870

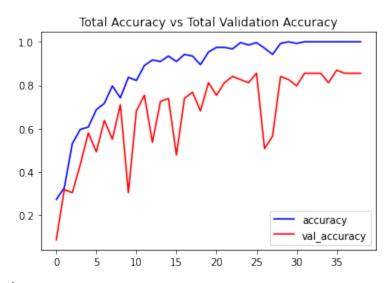
```
earlystop = EarlyStopping(monitor = 'val loss', patience = 10, mode = 'min', resto
 callbacks = [earlystop]
 history = model.fit(x = X_train, y = y_train, epochs=40, batch_size = 8 , shuffle=
Epoch 1/40
35/35 [============= ] - 42s 618ms/step - loss: 1.7920 - accuracy:
0.2347 - val_loss: 1.8170 - val_accuracy: 0.0870
Epoch 2/40
35/35 [=============== ] - 21s 589ms/step - loss: 1.6473 - accuracy:
0.3092 - val_loss: 1.4640 - val_accuracy: 0.3188
Epoch 3/40
35/35 [============== ] - 21s 589ms/step - loss: 1.3983 - accuracy:
0.4624 - val loss: 1.7697 - val accuracy: 0.3043
Epoch 4/40
35/35 [============== ] - 21s 589ms/step - loss: 1.1795 - accuracy:
0.6249 - val_loss: 1.4504 - val_accuracy: 0.4348
Epoch 5/40
35/35 [============= ] - 21s 589ms/step - loss: 1.1470 - accuracy:
0.5786 - val_loss: 1.1726 - val_accuracy: 0.5797
Epoch 6/40
35/35 [=============== ] - 21s 588ms/step - loss: 0.9869 - accuracy:
0.6695 - val_loss: 1.2644 - val_accuracy: 0.4928
Epoch 7/40
0.7069 - val_loss: 1.0360 - val_accuracy: 0.6377
Epoch 8/40
35/35 [============= ] - 21s 588ms/step - loss: 0.6390 - accuracy:
0.8102 - val_loss: 1.2429 - val_accuracy: 0.5507
Epoch 9/40
35/35 [============== ] - 21s 588ms/step - loss: 0.6633 - accuracy:
0.7116 - val_loss: 0.8459 - val_accuracy: 0.7101
Epoch 10/40
35/35 [============= ] - 21s 589ms/step - loss: 0.4606 - accuracy:
0.8476 - val_loss: 3.1645 - val_accuracy: 0.3043
Epoch 11/40
35/35 [============== ] - 21s 589ms/step - loss: 0.8911 - accuracy:
0.7713 - val loss: 0.9375 - val accuracy: 0.6812
Epoch 12/40
0.8862 - val_loss: 0.8197 - val_accuracy: 0.7536
Epoch 13/40
35/35 [============== ] - 21s 588ms/step - loss: 0.2840 - accuracy:
0.9068 - val_loss: 1.1775 - val_accuracy: 0.5362
Epoch 14/40
35/35 [============== ] - 21s 588ms/step - loss: 0.3360 - accuracy:
0.8886 - val_loss: 0.9045 - val_accuracy: 0.7246
Epoch 15/40
0.9493 - val loss: 0.8943 - val accuracy: 0.7391
Epoch 16/40
35/35 [============== ] - 21s 589ms/step - loss: 0.2404 - accuracy:
0.9146 - val_loss: 1.9742 - val_accuracy: 0.4783
Epoch 17/40
35/35 [============= ] - 21s 589ms/step - loss: 0.2938 - accuracy:
0.9193 - val loss: 0.8334 - val accuracy: 0.7391
Epoch 18/40
35/35 [============== ] - 21s 589ms/step - loss: 0.1470 - accuracy:
```

```
model evaluation history = model.evaluate(X test, y test) #Evaluate model on te
    from sklearn.metrics import classification_report #Produce report with extra met
    y_pred = model.predict(X_test, batch_size=4, verbose=1)
    y_pred = np.argmax(y_pred, axis = 1)
    y_test = np.argmax(y_test, axis = 1)
    print(classification report(y test, y pred))
22/22 [======== ] - 3s 93ms/step
             precision
                         recall f1-score
                                           support
                 0.74
                           0.91
          0
                                    0.82
                                               22
          1
                           0.86
                                    0.86
                                                7
                 0.86
          2
                 0.33
                          0.21
                                    0.26
                                               14
          3
                 0.86
                          0.67
                                    0.75
                                                9
          4
                          0.94
                                    0.86
                 0.80
                                               17
                                    0.97
                 1.00
                          0.94
                                               17
                                    0.78
                                               86
   accuracy
                 0.76
                           0.75
                                    0.75
                                               86
  macro avg
weighted avg
                 0.76
                           0.78
                                    0.76
                                               86
In...
   from sklearn.metrics import confusion_matrix #Produce confusion matrix to show @
   cm = confusion matrix(y test, y pred)
   print (cm)
[[20
                01
        0
          0 2
[ 0
     6
        1 0 0
                01
[ 7
             2
     1
        3
          1
                0]
  0 0
        3
          6 0
                01
          0 16 0]
  0
     0
       1
[ 0
        1
     0
          0 0 16]]
   def plot_metric(metric_name_1, metric_name_2, plot_name):
                                                                      # Fetch |
     metric_value_1 = history.history[metric_name_1]
     metric_value_2 = history.history[metric_name_2]
     epochs = range(len(metric_value_1))
                                                                       # Get epc
                                                                      # Plot Gi
     plt.plot(epochs, metric_value_1, 'blue', label = metric_name_1)
     plt.plot(epochs, metric_value_2, 'red', label = metric_name_2)
     plt.title(str(plot_name))
     plt.legend()
   plot_metric('loss', 'val_loss', 'Total Loss vs Total Validation Loss') #Plot Los
```

Total Loss vs Total Validation Loss



.... plot_metric('accuracy', 'val_accuracy', 'Total Accuracy vs Total Validation Accur



In ...
#evaluate on new different data set with similar classes

data dir2 = "UCF50/"

X1, Y1 = create_data(data_dir2) #use previous helper functions to extract frames

['Billiards', 'BenchPress', 'BreastStroke', 'Drumming', 'CleanAndJerk', 'BaseballPit ch', 'Basketball', 'HorseRiding', 'Kayaking', 'HighJump', 'JumpRope', 'JavelinThro w', 'HulaHoop', 'JugglingBalls', 'HorseRace', 'JumpingJack', 'PoleVault', 'Lunges', 'MilitaryParade', 'PlayingViolin', 'PlayingGuitar', 'PizzaTossing', 'Mixing', 'Nunch ucks', 'PlayingPiano', 'PlayingTabla', 'Skiing', 'SalsaSpin', 'PommelHorse', 'RockCl imbingIndoor', 'SkateBoarding', 'Rowing', 'RopeClimbing', 'PushUps', 'Swing', 'Skije t', 'SoccerJuggling', 'ThrowDiscus', 'WalkingWithDog', 'YoYo', 'TaiChi', 'TennisSwin g', 'VolleyballSpiking', 'TrampolineJumping', 'golf', 'ride_bike', 'fencing', 'div e', 'punch', 'pullup']

pullup Defected frame Defected frame punch Defected frame Defected frame

Defected frame

```
In [ ]:
    Eval_Hist = model.evaluate(X1, Y1) #evaluate on whole set from new dataset
0.4386
In...
   Y2 = model.predict(X1, batch_size=4, verbose=1) #produce extra metrics for predict
   Y2 = np.argmax(Y2, axis = 1)
   Y1 = np.argmax(Y1, axis = 1)
   print(classification_report(Y1, Y2))
206/206 [========= ] - 19s 92ms/step
            precision recall f1-score
         0
                0.35
                         0.64
                                  0.45
                                           118
                0.33
                                  0.11
         1
                         0.06
                                           156
         2
                0.38
                                  0.29
                         0.24
                                           152
         3
                0.07
                                  0.04
                         0.03
                                           111
         4
                0.41
                         0.86
                                  0.55
                                           145
         5
                0.82
                         0.79
                                  0.81
                                           141
   accuracy
                                  0.44
                                           823
                0.39
                         0.44
                                  0.38
                                           823
  macro avg
weighted avg
                0.41
                         0.44
                                  0.38
                                           823
   print(confusion_matrix(Y1, Y2)) #produce confusion matrix for prediction on new
[[ 76
          2
            2
                 8
                    19]
     11
[ 30
     10
         9 37 70
                    0]
      2 36
  71
             1 42
                    0]
[ 12
      6 32
            3 54
                    4]
[ 8
      1 11
             0 124
                     1]
```

[20

0

5 112]]