

“Cry” Detection Report

May 23 2020

1. Topic

My topic is “crying”.

2. Dataset

I replaced my previous dataset, which is self-crawled and consists of 151433 human facial images extracted from over 200 videos from Youtube, with a part of the STAIR actions dataset (<https://actions.stair.center/>). STAIR Actions is a video dataset consisting of 100 everyday human action categories. Each category contains around 900 to 1800 trimmed video clips. Each clip lasts 5 to 6 seconds. Clips are taken from YouTube video or made by crowdsource workers.

Kitchen related	
drinking	
eating meal	
eating snack	
washing dish	
throwing trash	
washing hands	
opening refrig door	
pouring tea or coffee	
cutting food	
cooking	
Washroom related	
setting hair	
drying hair with blower	
making up	
manicuring	
gargling	
brushing teeth	
washing face	
shaving	
Object manipulation	
wearing glass	
playing with toy	
playing board game	
using computer	
listening to music with headphones	
playing computer game	
taking photo	
using smartphone	
using tablet	
operating remote control	
watching TV	
telephoning	
gardening	
playing guitar	
playing piano	
blowing flute	
standing on chair or table or stepladder	
throwing	
opening or closing container	
smoking	
ironing	
knitting or stitching	
polishing shoe	
wearing shoes	
sewing	
hanging out or capture laundry	
folding laundry	
wearing tie	
putting off cloth	
putting on cloth	
housecleaning	
wiping window	
drawing picture	
doing origami	
reading newspaper	
studying	
reading book	
writing	

Multiplayer action
changing baby diaper
bottle-feeding baby
piggybacking someone
holding someone
feeding baby
assisting in getting up
assisting in walking
teaching
nodding
shaking head
speaking
hearing
pointing with finger
caressing head
kissing
doing high five
hugging
stroking animal
shaking hands
bowing
giving massage
passing something
doing paper-rock-scissors
fighting
Solo action
walking with stick
walking
going up or down stairs
jumping on sofa or bed
baby crying
baby crawling
exercising
dancing
running around
clapping hands
sitting down
standing up
sleeping on bed
lying on floor
leaving room
entering room
being angry
being surprised
crying
smiling

I downloaded 1890 video clips from the STAIRS actions dataset, including all crying video clips and an equal amount of negative ones which cover almost all the actions shown in the above picture. I picked 1393 qualified videos from the downloaded ones and extract the face, hand and pose landmarks from the videos using OpenPose. In this way I created a dataset of 177925 rows of face, hand and pose data. After balancing positives and negatives, the size of the dataset became 149102, consisting of 74665 positives and 74437 negatives.

I also created 2 more dataset based on my original dataset, one consisting of pose data only and one consisting of face and hand data only. The pose dataset is of size 82323, consisting of 41165 positives and 41158 negatives. The face and hand dataset is of size 26686, with 16551 positives and 15124 negatives.

3. Model

I tried 3 models selected from my previous models and used different data to train these models. At first, I used face-pose-hand data, but the performance is not good. I think the reason is that few positive videos record the whole body of a person, and they either record people above shoulder or the whole body with face and hands difficult to be recognized by OpenPose. Also, if the video dose not contain elbows, the hand data will not be extracted by OpenPose. So, the data extracted contain many 0s, which may disrupt the model. Therefore, I created 2 more dataset based on my original dataset, one consisting of pose data only and one consisting of face and hand data only.

1. 2D CNN model (trained with face-pose-hand data)

This model has 3 convolutional layers, 2 fully connected layers and 1 binary classification layer. I take every 10 frames as a timestep. My origin input data is of size (149102, 10, 274), in order to fit it into this model, I deleted 24 columns that has the most 0s and dropped several samples that has too many 0s, and get an input of size (126065, 10, 250), and then reshaped it into (126065, 50, 50, 1).

```
9 def create_model():
10     #1st convolution layer
11     model = Sequential()
12
13     model.add(Conv2D(64, kernel_size=(3, 3), activation='relu', input_shape=(X_train_4.shape[1:]
14     model.add(Conv2D(64, kernel_size= (3, 3), activation='relu'))
15     # model.add(BatchNormalization())
16     model.add(MaxPooling2D(pool_size=(2,2), strides=(2, 2)))
17     model.add(Dropout(0.5))
18
19     #2nd convolution layer
20     model.add(Conv2D(64, (3, 3), activation='relu'))
21     model.add(Conv2D(64, (3, 3), activation='relu'))
22     # model.add(BatchNormalization())
23     model.add(MaxPooling2D(pool_size=(2,2), strides=(2, 2)))
24     model.add(Dropout(0.5))
```

```

25
26 #3rd convolution layer
27 model.add(Conv2D(128, (3, 3), activation='relu'))
28 model.add(Conv2D(128, (3, 3), activation='relu'))
29 # model.add(BatchNormalization())
30 model.add(MaxPooling2D(pool_size=(2,2), strides=(2, 2)))
31
32 model.add(Flatten())
33
34 #fully connected neural networks
35 model.add(Dense(1024, activation='relu'))
36 model.add(Dropout(0.2))
37 model.add(Dense(1024, activation='relu'))
38 model.add(Dropout(0.2))
39
40 model.add(Dense(1, activation='sigmoid'))
41 # model.summary()
42
43 #Compiling the model
44 model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
45 return model
46

```

Model Summary:

Model: "sequential_29"

Layer (type)	Output Shape	Param #
conv2d_40 (Conv2D)	(None, 48, 48, 64)	640
conv2d_41 (Conv2D)	(None, 46, 46, 64)	36928
max_pooling2d_18 (MaxPooling)	(None, 23, 23, 64)	0
dropout_49 (Dropout)	(None, 23, 23, 64)	0
conv2d_42 (Conv2D)	(None, 21, 21, 64)	36928
conv2d_43 (Conv2D)	(None, 19, 19, 64)	36928
max_pooling2d_19 (MaxPooling)	(None, 9, 9, 64)	0
dropout_50 (Dropout)	(None, 9, 9, 64)	0
conv2d_44 (Conv2D)	(None, 7, 7, 128)	73856
conv2d_45 (Conv2D)	(None, 5, 5, 128)	147584
max_pooling2d_20 (MaxPooling)	(None, 2, 2, 128)	0
flatten_9 (Flatten)	(None, 512)	0
dense_42 (Dense)	(None, 1024)	525312
dropout_51 (Dropout)	(None, 1024)	0
dense_43 (Dense)	(None, 1024)	1049600
dropout_52 (Dropout)	(None, 1024)	0
dense_44 (Dense)	(None, 1)	1025
Total params: 1,908,801		
Trainable params: 1,908,801		
Non-trainable params: 0		

2. 1D CNN model (trained with pose data)

This model has 3 convolutional layers, 2 fully connected layers and 1 binary classification layer.

I tried only pose data to train this model. I deleted several samples that has more than 124 0s, and then take every 15 frames as a timestep, and created an input of size (82323, 15, 50).

```
1 def create_model_1(X_train):
2     model = Sequential()
3
4     model.add(Conv1D(32, 3, padding = 'same', input_shape=(X_train.shape[1:])))
5     model.add(BatchNormalization())
6     model.add(Activation('relu'))
7     model.add(Conv1D(32, 3, padding = 'same'))
8     model.add(BatchNormalization())
9
10    model.add(Conv1D(64, 3, padding = 'same'))
11    model.add(BatchNormalization())
12    model.add(Activation('relu'))
13    model.add(Conv1D(64, 3, padding = 'same'))
14    model.add(BatchNormalization())
15
16    model.add(Conv1D(64, 3, padding = 'same'))
17    model.add(BatchNormalization())
18    model.add(Activation('relu'))
19    model.add(Conv1D(64, 3, padding = 'same'))
20    model.add(BatchNormalization())
21
22    model.add(GlobalAveragePooling1D())
23
24    model.add(Dense(128, activation='relu'))
25    model.add(Dropout(0.2))
26
27    model.add(Dense(128, activation = 'relu'))
28    model.add(Dropout(0.2))
29    model.add(Dense(1, activation='sigmoid'))
30    model.summary()
31    model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
32    return model
```

Model Summary:

Layer (type)	Output Shape	Param #
=====		
conv1d_1 (Conv1D)	(None, 15, 32)	4832
batch_normalization_1 (Batch Normalization)	(None, 15, 32)	128
activation_1 (Activation)	(None, 15, 32)	0
conv1d_2 (Conv1D)	(None, 15, 32)	3104
batch_normalization_2 (Batch Normalization)	(None, 15, 32)	128

conv1d_3 (Conv1D)	(None, 15, 64)	6208
batch_normalization_3 (Batch Normalization)	(None, 15, 64)	256
activation_2 (Activation)	(None, 15, 64)	0
conv1d_4 (Conv1D)	(None, 15, 64)	12352
batch_normalization_4 (Batch Normalization)	(None, 15, 64)	256
conv1d_5 (Conv1D)	(None, 15, 64)	12352
batch_normalization_5 (Batch Normalization)	(None, 15, 64)	256
activation_3 (Activation)	(None, 15, 64)	0
conv1d_6 (Conv1D)	(None, 15, 64)	12352
batch_normalization_6 (Batch Normalization)	(None, 15, 64)	256
global_average_pooling1d_1 (Global Average Pooling1D)	(None, 64)	0
dense_7 (Dense)	(None, 128)	8320
dropout_7 (Dropout)	(None, 128)	0
dense_8 (Dense)	(None, 128)	16512
dropout_8 (Dropout)	(None, 128)	0
dense_9 (Dense)	(None, 1)	129
=====		
Total params: 77,441		
Trainable params: 76,801		
Non-trainable params: 640		

3. LSTM model (trained with face-hand data)

This model has 3 LSTM layers and 1 binary classification layer.

I tried face and hand data to train this model. I deleted several samples that has more than 84 0s (which means no hand data), and then take every 20 frames as a timestep, and created an input of size (26686, 20, 134).

```

1 def create_model_1():
2     model = Sequential()
3     model.add(Dense(units = 32, input_shape=(TIME_STEP, INPUT_DIM), activation='relu'))
4     model.add(CuDNNLSTM(units = 32, input_shape=(TIME_STEP, INPUT_DIM), return_sequences = True))
5     model.add(Dropout(DROPOUT))
6     model.add(CuDNNLSTM(units = 32, input_shape=(TIME_STEP, INPUT_DIM), return_sequences = True))
7     model.add(Dropout(DROPOUT))
8     model.add(CuDNNLSTM(units = 32))
9     model.add(Dense(1, activation='sigmoid'))
10    model.summary()
11    model.compile(optimizer=rmsprop, loss='binary_crossentropy', metrics=['acc'])
12    return model

```

Model Summary:

Layer (type)	Output Shape	Param #
dense_7 (Dense)	(None, 20, 32)	7200
cu_dnnlstm_10 (CuDNNLSTM)	(None, 20, 32)	8448
dropout_7 (Dropout)	(None, 20, 32)	0
cu_dnnlstm_11 (CuDNNLSTM)	(None, 20, 32)	8448
dropout_8 (Dropout)	(None, 20, 32)	0
cu_dnnlstm_12 (CuDNNLSTM)	(None, 32)	8448
dense_8 (Dense)	(None, 1)	33
Total params: 32,577		
Trainable params: 32,577		
Non-trainable params: 0		

4. Performance and analysis

1. 2D CNN model

I tuned the batch size and find that 64 is optimal.

Result:

```
1 model_b = create_model()
2 model_b.summary()
3 history_b = model_b.fit(X_train_4, y_train, epochs=50, batch_size=64,
4                         validation_split=0.15, verbose=2, callbacks=callbacks_list)
```

Train on 107155 samples, validate on 18910 samples

Epoch 1/50

- 45s - loss: 0.3840 - acc: 0.8205 - val_loss: 0.4019 - val_acc: 0.8352

Epoch 2/50

- 44s - loss: 0.2070 - acc: 0.9128 - val_loss: 0.4120 - val_acc: 0.8570

Epoch 3/50

- 44s - loss: 0.1441 - acc: 0.9420 - val_loss: 0.4535 - val_acc: 0.8640

Epoch 4/50

- 44s - loss: 0.1109 - acc: 0.9572 - val_loss: 0.4268 - val_acc: 0.8702

Epoch 5/50

- 44s - loss: 0.0891 - acc: 0.9662 - val_loss: 0.4439 - val_acc: 0.8780

Epoch 6/50

- 44s - loss: 0.0741 - acc: 0.9718 - val_loss: 0.6538 - val_acc: 0.8501

Epoch 00006: early stopping

Figure about training and validation accuracy:

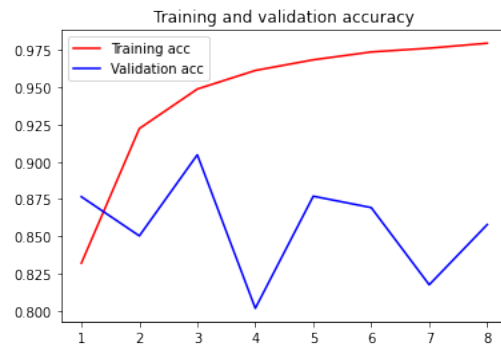


Figure about training and validation loss:



Loss and accuracy on test set:

```
1 score_b = model_b.evaluate(X_test_4, y_test, verbose=2)
2 print(score_b)
```

[0.9702688392152429, 0.8499804735183716]

2. 1D CNN model

I tuned batch size, time step, train-validation split and dropout, and find batch size = 32, time step = 15, train-validation split = 0.2, dropout = 0.2 to be optimal.

Result:

```
1 # create model
2 model_1 = create_model_1(X_train)
3 history = model_1.fit(X_train, y_train, epochs=EPOCH, batch_size=32,
4                       validation_split=0.2, verbose=2, callbacks=callbacks_list)
5 score = model_1.evaluate(X_test, y_test, verbose=2)
6 print("test loss: ", score[0], "test acc: ", score[1])
```

```
Epoch 1/100
- 22s - loss: 0.2806 - acc: 0.8874 - val_loss: 0.2119 - val_acc: 0.9192
Epoch 2/100
- 20s - loss: 0.1724 - acc: 0.9351 - val_loss: 0.3051 - val_acc: 0.8964
Epoch 3/100
- 21s - loss: 0.1414 - acc: 0.9488 - val_loss: 0.1299 - val_acc: 0.9563
Epoch 4/100
- 20s - loss: 0.1167 - acc: 0.9576 - val_loss: 0.0714 - val_acc: 0.9725
Epoch 5/100
- 20s - loss: 0.1042 - acc: 0.9634 - val_loss: 0.0642 - val_acc: 0.9752
Epoch 6/100
- 21s - loss: 0.0935 - acc: 0.9675 - val_loss: 0.0714 - val_acc: 0.9745
Epoch 7/100
- 20s - loss: 0.0831 - acc: 0.9711 - val_loss: 0.0670 - val_acc: 0.9759
Epoch 8/100
- 20s - loss: 0.0743 - acc: 0.9739 - val_loss: 0.0229 - val_acc: 0.9911
Epoch 9/100
- 21s - loss: 0.0713 - acc: 0.9762 - val_loss: 0.0559 - val_acc: 0.9813
Epoch 10/100
- 20s - loss: 0.0686 - acc: 0.9773 - val_loss: 0.0462 - val_acc: 0.9834
Epoch 11/100
- 20s - loss: 0.0642 - acc: 0.9789 - val_loss: 0.0153 - val_acc: 0.9948
Epoch 12/100
- 21s - loss: 0.0642 - acc: 0.9785 - val_loss: 0.0319 - val_acc: 0.9903
Epoch 13/100
- 20s - loss: 0.0620 - acc: 0.9804 - val_loss: 0.0361 - val_acc: 0.9902
Epoch 14/100
- 20s - loss: 0.0556 - acc: 0.9815 - val_loss: 0.0741 - val_acc: 0.9702
Epoch 15/100
- 21s - loss: 0.0544 - acc: 0.9824 - val_loss: 0.0157 - val_acc: 0.9954
Epoch 16/100
- 20s - loss: 0.0534 - acc: 0.9825 - val_loss: 0.0485 - val_acc: 0.9895
Epoch 17/100
- 21s - loss: 0.0508 - acc: 0.9840 - val_loss: 0.0761 - val_acc: 0.9745

Epoch 18/100
- 20s - loss: 0.0480 - acc: 0.9847 - val_loss: 0.0128 - val_acc: 0.9968
Epoch 19/100
- 20s - loss: 0.0502 - acc: 0.9851 - val_loss: 0.0082 - val_acc: 0.9970
Epoch 20/100
- 20s - loss: 0.0464 - acc: 0.9857 - val_loss: 0.0134 - val_acc: 0.9954
Epoch 21/100
- 20s - loss: 0.0445 - acc: 0.9866 - val_loss: 0.0601 - val_acc: 0.9850
Epoch 22/100
- 20s - loss: 0.0462 - acc: 0.9859 - val_loss: 0.0823 - val_acc: 0.9796
Epoch 23/100
- 20s - loss: 0.0415 - acc: 0.9870 - val_loss: 0.0076 - val_acc: 0.9978
Epoch 24/100
- 20s - loss: 0.0453 - acc: 0.9864 - val_loss: 0.0105 - val_acc: 0.9972
Epoch 25/100
- 21s - loss: 0.0393 - acc: 0.9876 - val_loss: 0.0465 - val_acc: 0.9851
Epoch 26/100
- 21s - loss: 0.0392 - acc: 0.9878 - val_loss: 0.0131 - val_acc: 0.9971
Epoch 27/100
- 21s - loss: 0.0408 - acc: 0.9878 - val_loss: 0.0111 - val_acc: 0.9966
Epoch 28/100
- 21s - loss: 0.0377 - acc: 0.9892 - val_loss: 0.0061 - val_acc: 0.9982
Epoch 00028: early stopping
```


Figure about training and validation accuracy:

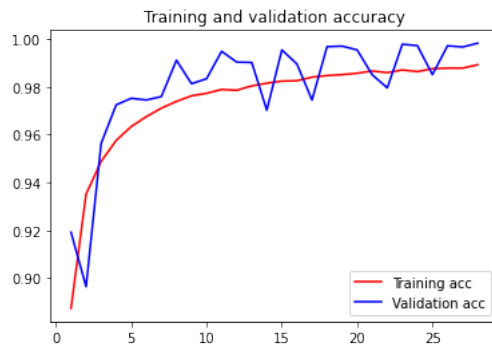
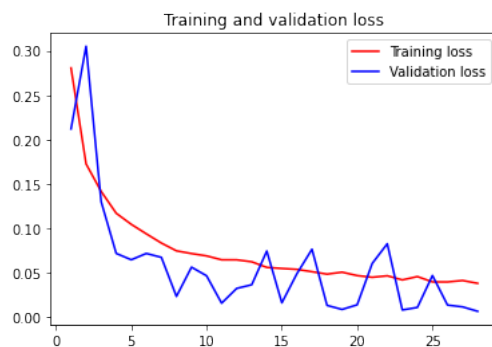


Figure about training and validation loss:



Accuracy and loss on test set:

```
Epoch 25/25: 1.0799628502802385 test loss:  0.837231457233429
```

3. LSTM model

I tuned Dense units, LSTM units, batch size, time step, train-validation split and dropout, and find units = 32, batch size = 32, time step = 20, train-validation split = 0.2, dropout = 0.5 to be optimal.

Result:

```
1 # create model
2 model_1 = create_model_1()
3 history = model_1.fit(X_train_20, y_train, epochs=EPOCH, batch_size=32,
4                       validation_split=0.2, verbose=2, callbacks=callbacks_list)
5 score = model_1.evaluate(X_test_20, y_test, verbose=2)
6 print("test loss: ", score[0], "test acc: ", score[1])
```

```
Epoch 1/100
- 6s - loss: 0.3732 - acc: 0.8367 - val_loss: 0.4272 - val_acc: 0.8331
Epoch 2/100
- 5s - loss: 0.2366 - acc: 0.8992 - val_loss: 0.1817 - val_acc: 0.9240
Epoch 3/100
- 5s - loss: 0.1832 - acc: 0.9209 - val_loss: 0.1494 - val_acc: 0.9368
Epoch 4/100
- 5s - loss: 0.1509 - acc: 0.9387 - val_loss: 0.1202 - val_acc: 0.9559
Epoch 5/100
- 5s - loss: 0.1262 - acc: 0.9508 - val_loss: 0.1264 - val_acc: 0.9576
Epoch 6/100
- 5s - loss: 0.1059 - acc: 0.9610 - val_loss: 0.1362 - val_acc: 0.9535
Epoch 7/100
- 5s - loss: 0.0878 - acc: 0.9696 - val_loss: 0.0599 - val_acc: 0.9829
Epoch 8/100
- 5s - loss: 0.0764 - acc: 0.9742 - val_loss: 0.0661 - val_acc: 0.9801

Epoch 9/100
- 5s - loss: 0.0690 - acc: 0.9775 - val_loss: 0.0363 - val_acc: 0.9884
Epoch 10/100
- 5s - loss: 0.0572 - acc: 0.9812 - val_loss: 0.0709 - val_acc: 0.9742
Epoch 11/100
- 5s - loss: 0.0577 - acc: 0.9830 - val_loss: 0.0333 - val_acc: 0.9867
Epoch 12/100
- 5s - loss: 0.0505 - acc: 0.9843 - val_loss: 0.0308 - val_acc: 0.9895
Epoch 13/100
- 5s - loss: 0.0468 - acc: 0.9858 - val_loss: 0.0252 - val_acc: 0.9913
Epoch 14/100
- 5s - loss: 0.0442 - acc: 0.9864 - val_loss: 0.0186 - val_acc: 0.9935
Epoch 15/100
- 5s - loss: 0.0503 - acc: 0.9861 - val_loss: 0.0173 - val_acc: 0.9947
Epoch 16/100
- 5s - loss: 0.0399 - acc: 0.9878 - val_loss: 0.0386 - val_acc: 0.9893
Epoch 17/100
- 5s - loss: 0.0361 - acc: 0.9893 - val_loss: 0.0119 - val_acc: 0.9959
Epoch 18/100
- 5s - loss: 0.0375 - acc: 0.9893 - val_loss: 0.0095 - val_acc: 0.9970
Epoch 19/100
- 5s - loss: 0.0323 - acc: 0.9906 - val_loss: 0.0498 - val_acc: 0.9875
Epoch 20/100
- 5s - loss: 0.0324 - acc: 0.9906 - val_loss: 0.0352 - val_acc: 0.9880
Epoch 21/100
- 5s - loss: 0.0369 - acc: 0.9902 - val_loss: 0.0143 - val_acc: 0.9967
Epoch 22/100
- 5s - loss: 0.0279 - acc: 0.9927 - val_loss: 0.0237 - val_acc: 0.9924
Epoch 23/100
- 5s - loss: 0.0300 - acc: 0.9917 - val_loss: 0.0114 - val_acc: 0.9963
Epoch 00023: early stopping
```

Figure about training and validation accuracy:

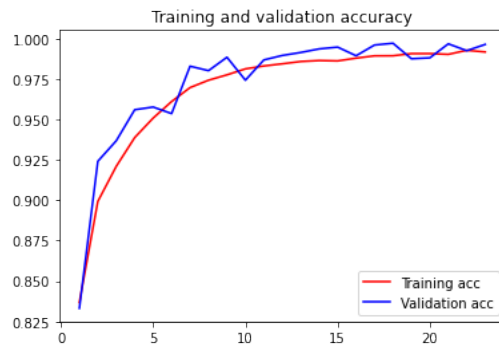
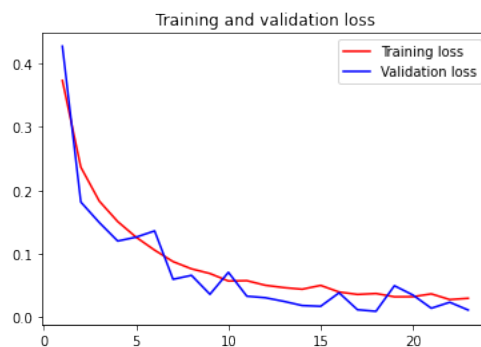


Figure about training and validation loss:



Accuracy and loss on test set:

test loss: 0.5815535898602696 test acc: 0.8855501413345337

5. Instructions on how to test my code

1. My codes on Github: <https://github.com/YiranH/Cry-Detection-in-Real-Time.git>
2. My codes and data on Google Colab:

<https://drive.google.com/open?id=17LOBLJLDFgHtDvpQV39D5OBpooPrtlvy>

Demo code on Google Colab:

<https://drive.google.com/open?id=10b7DBiOGlapxjjlYHh6pCj6xQllf8aaB>

Training code:

<https://drive.google.com/open?id=1T3SIWggkeZrPx4Iezw9qOGjeo2iUIU8i>

https://drive.google.com/open?id=1PvS18tl3G0RnAdE_7euRV8MI_1YI6UfS

https://drive.google.com/open?id=1rch_iFtvEwpTTF8f8Lwd1GsEAgKH1QtM

3. My sample videos are the last 5 test videos sent to me, and the figures and json files are generated by the LSTM model.

- 8) 1600_4, <https://youtu.be/0mc6IJd0NEw>
- 9) 1700_2, <https://youtu.be/LqRJSNM814g>
- 10) 1800_2, <https://youtu.be/IS3YZ9JSsnc>
- 11) 1900_2, <https://youtu.be/UUtdMuT1EBU>
- 12) 2000_2, <https://youtu.be/NEkWx0pmzq4>