

```
In [1]: !git clone https://github.com/ksideks/UCSD.git
```

fatal: docelowa ścieżka „UCSD” już istnieje i nie jest pustym katalogiem.

```
In [2]: !pip install keras-layer-normalization
```

Requirement already satisfied: keras-layer-normalization in ./jupyterenv/lib/python3.8/site-packages (0.15.0)  
Requirement already satisfied: Keras in ./jupyterenv/lib/python3.8/site-packages (from keras-layer-normalization) (2.7.0)  
Requirement already satisfied: numpy in ./jupyterenv/lib/python3.8/site-packages (from keras-layer-normalization) (1.21.3)

```
In [3]: TestVideoFile = {}
TestVideoFile[1] = range(59,152)
TestVideoFile[2] = range(49,175)
TestVideoFile[3] = range(90,200)
TestVideoFile[4] = range(30,168)
TestVideoFile[5] = list(range(4,90)) + list(range(139,200))
TestVideoFile[6] = list(range(0,100)) + list(range(109,200))
TestVideoFile[7] = range(0,175)
TestVideoFile[8] = range(0,94)
TestVideoFile[9] = range(0,48)
TestVideoFile[10] = range(0,140)
TestVideoFile[11] = range(69,165)
TestVideoFile[12] = range(130,200)
TestVideoFile[13] = range(0,156)
TestVideoFile[14] = range(3,198) # 0 200
TestVideoFile[15] = range(137,200)
TestVideoFile[16] = range(122,200)
TestVideoFile[17] = range(0,47)
TestVideoFile[18] = range(53,120)
TestVideoFile[19] = range(63,138)
TestVideoFile[20] = range(44,175)
TestVideoFile[21] = range(30,200)
TestVideoFile[22] = range(16,107)
TestVideoFile[23] = range(8,165)
TestVideoFile[24] = range(49,171)
TestVideoFile[25] = range(39,135)
TestVideoFile[26] = range(77,144)
TestVideoFile[27] = range(9,122)
TestVideoFile[28] = range(104,200)
TestVideoFile[29] = list(range(0,15)) + list(range(44,113))
TestVideoFile[30] = range(174,200)
TestVideoFile[31] = range(0,180)
TestVideoFile[32] = list(range(0,52)) + list(range(64,115))
TestVideoFile[33] = range(4,165)
TestVideoFile[34] = range(0,121)
TestVideoFile[35] = range(85,200)
TestVideoFile[36] = range(14,108)
```

In [4]:

```
#imports
from os import listdir
from os.path import isfile, join, isdir
from PIL import Image
import numpy as np
import shelve

import keras
import tensorflow as tf
from keras.layers import Conv2DTranspose, ConvLSTM2D, BatchNormalization,
from keras.models import Sequential, load_model

from os import listdir
from os.path import isfile, join, isdir
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import metrics
```

2021-11-10 19:47:51.170952: W tensorflow/stream\_executor/platform/default/dso\_loader.cc:64] Could not load dynamic library 'libcudart.so.11.0'; dlerro  
r: libcudart.so.11.0: cannot open shared object file: No such file or direc  
tory  
2021-11-10 19:47:51.170997: I tensorflow/stream\_executor/cuda/cudart\_stub.c  
c:29] Ignore above cudart dlerror if you do not have a GPU set up on your m  
achine.

In [5]:

```
class Config:
    DATASET_PATH = "UCSD/UCSD_Anomaly_Dataset.v1p2/UCSDped1/Train"
    TEST_PATH = "UCSD/UCSD_Anomaly_Dataset.v1p2/UCSDped1/Test"
    SINGLE_TEST_PATH = "UCSD/UCSD_Anomaly_Dataset.v1p2/UCSDped1/Test/Test001"
    SINGLE_TEST_VIDEO_FILE = 1
    BATCH_SIZE = 32
    EPOCHS = 50
    MODEL_PATH = "UCSD/model.hdf5"
    THRESHOLD = 0.95
```

In [6]:

```
def get_clips_by_step(step, frames_list, sequence_size):  
  
    #data pre-processing, one volume has 10 clips, with different steps (1  
    volumes = []  
    size = len(frames_list)  
    clip = np.zeros(shape=(sequence_size, 227, 227, 1))  
    cnt = 0  
    for start in range(0, step):  
        for i in range(start, size, step):  
            clip[cnt, :, :, 0] = frames_list[i]  
            cnt = cnt + 1  
            if cnt == sequence_size:  
                volumes.append(np.copy(clip))  
                cnt = 0  
    return volumes  
  
def get_training_set():  
    clips = []  
    for f in sorted(listdir(Config.DATASET_PATH)):  
        if isdir(join(Config.DATASET_PATH, f)):  
            all_frames = []  
            for c in sorted(listdir(join(Config.DATASET_PATH, f))):  
                if str(join(join(Config.DATASET_PATH, f), c))[-3:] == ".tif":  
                    img = Image.open(join(join(Config.DATASET_PATH, f), c))  
                    img = np.array(img, dtype=np.float32) / 256.0  
                    all_frames.append(img)  
            for stride in range(1, 3):  
                clips.extend(get_clips_by_step(step=stride, frames_list=all_frames))  
    return clips
```

In [7]:

```

def get_model(reload_model=True):

    #model is already saved, there's possibility to retrain it, but not until
    if not reload_model:
        return load_model(Config.MODEL_PATH, custom_objects={'LayerNormalization': LayerNormalization})

    #adding print checkpoints to see if model works
    print("starting training")
    training_set = get_training_set()
    training_set = np.array(training_set)
    print("got training set")

    training_set = training_set.reshape(-1, 10, 227, 227, 1)

    seq = Sequential()

    #AUTOENCODER --> spatial part

    seq.add(TimeDistributed(Conv2D(128, (11, 11), strides=4, padding="valid")))
    seq.add(LayerNormalization())
    seq.add(TimeDistributed(Conv2D(64, (5, 5), strides=2, padding="valid")))
    seq.add(LayerNormalization())

    # Convolutional Long-short term memory --> temporal part
    seq.add(ConvLSTM2D(64, (3, 3), strides=1, padding="same", return_sequences=True))
    seq.add(LayerNormalization())
    seq.add(ConvLSTM2D(32, (3, 3), strides=1, padding="same", return_sequences=True))
    seq.add(LayerNormalization())
    seq.add(ConvLSTM2D(64, (3, 3), strides=1, padding="same", return_sequences=True))
    seq.add(LayerNormalization())

    # AUTODECODER --> spatial part

    seq.add(TimeDistributed(Conv2DTranspose(128, (5, 5), strides=2, padding="valid")))
    seq.add(LayerNormalization())
    seq.add(TimeDistributed(Conv2DTranspose(1, (11, 11), strides=4, padding="valid")))
    seq.add(LayerNormalization())
    #seq.add(TimeDistributed(Conv2D(1, (11, 11), activation="sigmoid", padding="valid")))

    print(seq.summary()) # SUMMARY Should be visible /seq.summary()

    seq.compile(loss='mse', optimizer=tf.keras.optimizers.Adam(lr=1e-3)) #
    seq.fit(training_set, training_set,
            batch_size=Config.BATCH_SIZE, epochs=Config.EPOCHS, shuffle=False)
    seq.save(Config.MODEL_PATH)
    return seq

```

In [8]:

```
def get_single_test():
    size = 200
    test = np.zeros(shape=(size, 227, 227, 1))
    cnt = 0
    for f in sorted.listdir(Config.SINGLE_TEST_PATH):
        if str(join(Config.SINGLE_TEST_PATH, f))[-3:] == ".tif":
            img = Image.open(join(Config.SINGLE_TEST_PATH, f)).resize((227, 227))
            img = np.array(img, dtype=np.float32) / 256.0
            test[cnt, :, :, 0] = img
            cnt = cnt + 1
    return test
```

In [9]:

```
def evaluate(reload_model=False):
    model = get_model(reload_model) #get_model(True) ->to retrain the model
    print("got model")
    test = get_single_test()
    print(test.shape)
    size = test.shape[0] - 10 + 1
    sequences = np.zeros((size, 10, 227, 227, 1))
    # apply the sliding window technique to get the sequences
    for i in range(0, size):
        clip = np.zeros((10, 227, 227, 1))
        for j in range(0, 10):
            clip[j] = test[i + j, :, :, :]
        sequences[i] = clip

    print("got data")

    # get the reconstruction cost of all the sequences
    reconstructed_sequences = model.predict(sequences, batch_size=4)

    #calculating the Eculidean distance/norm2
    sequences_reconstruction_cost = np.array([np.linalg.norm(np.subtract(s, r)) for s, r in zip(sequences, reconstructed_sequences)])

    #anomaly score as = sa
    anomaly_score = (sequences_reconstruction_cost - np.min(sequences_reconstruction_cost)) / (sequences_reconstruction_cost - np.min(sequences_reconstruction_cost))

    #Regularity score -> sr
    regularity_score = 1.0 - anomaly_score

    # plot the regularity scores vs frames
    plt.plot(regularity_score)
    plt.ylabel('regularity score(t)')
    plt.xlabel('frame t')
    plt.show()

    return regularity_score
```

In [10]:

```
pr = evaluate(reload_model=True) #checking for one video
```

starting training

got training set

```
2021-11-10 19:48:11.026840: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'libcuda.so.1'; dlerror: libcuda.so.1: cannot open shared object file: No such file or directory
2021-11-10 19:48:11.026896: W tensorflow/stream_executor/cuda/cuda_driver.cc:269] failed call to cuInit: UNKNOWN ERROR (303)
2021-11-10 19:48:11.026928: I tensorflow/stream_executor/cuda/cuda_diagnost
```

```
ics.cc:156] kernel driver does not appear to be running on this host (ml):
/proc/driver/nvidia/version does not exist
2021-11-10 19:48:11.027374: I tensorflow/core/platform/cpu_feature_guard.c
c:151] This TensorFlow binary is optimized with oneAPI Deep Neural Network
Library (oneDNN) to use the following CPU instructions in performance-criti
cal operations: AVX2 AVX512F FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
Model: "sequential"
```

Layer (type)	Output Shape	Param #
time_distributed (TimeDistributed)	(None, 10, 55, 55, 128)	15616
layer_normalization (LayerNormalization)	(None, 10, 55, 55, 128)	256
time_distributed_1 (TimeDistributed)	(None, 10, 26, 26, 64)	204864
layer_normalization_1 (LayerNormalization)	(None, 10, 26, 26, 64)	128
conv_lstm2d (ConvLSTM2D)	(None, 10, 26, 26, 64)	295168
layer_normalization_2 (LayerNormalization)	(None, 10, 26, 26, 64)	128
conv_lstm2d_1 (ConvLSTM2D)	(None, 10, 26, 26, 32)	110720
layer_normalization_3 (LayerNormalization)	(None, 10, 26, 26, 32)	64
conv_lstm2d_2 (ConvLSTM2D)	(None, 10, 26, 26, 64)	221440
layer_normalization_4 (LayerNormalization)	(None, 10, 26, 26, 64)	128
time_distributed_2 (TimeDistributed)	(None, 10, 55, 55, 128)	204928
layer_normalization_5 (LayerNormalization)	(None, 10, 55, 55, 128)	256
time_distributed_3 (TimeDistributed)	(None, 10, 227, 227, 1)	15489
layer_normalization_6 (LayerNormalization)	(None, 10, 227, 227, 1)	2

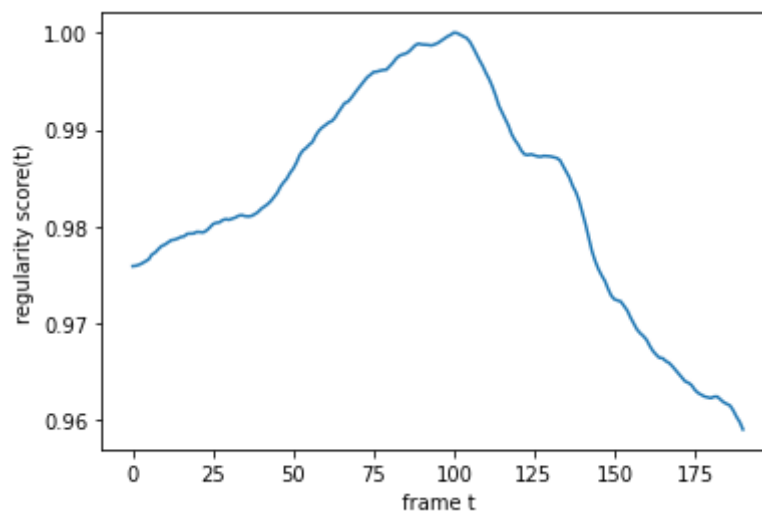
```
=====  
Total params: 1,069,187  
Trainable params: 1,069,187  
Non-trainable params: 0
```

```
None
```

```
/home/user/notebook/jupyterenv/lib/python3.8/site-packages/keras/optimizer_v2/adam.py:105: UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.  
super(Adam, self).__init__(name, **kwargs)  
Epoch 1/50  
43/43 [=====] - 492s 11s/step - loss: 0.1657
```

```
Epoch 2/50
43/43 [=====] - 478s 11s/step - loss: 0.1382
Epoch 3/50
43/43 [=====] - 484s 11s/step - loss: 0.1155
Epoch 4/50
43/43 [=====] - 480s 11s/step - loss: 0.0971
Epoch 5/50
43/43 [=====] - 490s 11s/step - loss: 0.0825
Epoch 6/50
43/43 [=====] - 474s 11s/step - loss: 0.0711
Epoch 7/50
43/43 [=====] - 483s 11s/step - loss: 0.0624
Epoch 8/50
43/43 [=====] - 470s 11s/step - loss: 0.0559
Epoch 9/50
43/43 [=====] - 482s 11s/step - loss: 0.0511
Epoch 10/50
43/43 [=====] - 474s 11s/step - loss: 0.0477
Epoch 11/50
43/43 [=====] - 477s 11s/step - loss: 0.0453
Epoch 12/50
43/43 [=====] - 477s 11s/step - loss: 0.0437
Epoch 13/50
43/43 [=====] - 472s 11s/step - loss: 0.0427
Epoch 14/50
43/43 [=====] - 483s 11s/step - loss: 0.0420
Epoch 15/50
43/43 [=====] - 467s 11s/step - loss: 0.0416
Epoch 16/50
43/43 [=====] - 482s 11s/step - loss: 0.0413
Epoch 17/50
43/43 [=====] - 469s 11s/step - loss: 0.0411
Epoch 18/50
43/43 [=====] - 480s 11s/step - loss: 0.0411
Epoch 19/50
43/43 [=====] - 470s 11s/step - loss: 0.0410
Epoch 20/50
43/43 [=====] - 469s 11s/step - loss: 0.0410
Epoch 21/50
43/43 [=====] - 470s 11s/step - loss: 0.0410
Epoch 22/50
43/43 [=====] - 467s 11s/step - loss: 0.0410
Epoch 23/50
43/43 [=====] - 476s 11s/step - loss: 0.0410
Epoch 24/50
43/43 [=====] - 465s 11s/step - loss: 0.0410
Epoch 25/50
43/43 [=====] - 478s 11s/step - loss: 0.0410
Epoch 26/50
43/43 [=====] - 463s 11s/step - loss: 0.0410
Epoch 27/50
43/43 [=====] - 474s 11s/step - loss: 0.0410
Epoch 28/50
43/43 [=====] - 467s 11s/step - loss: 0.0410
Epoch 29/50
43/43 [=====] - 468s 11s/step - loss: 0.0410
Epoch 30/50
43/43 [=====] - 472s 11s/step - loss: 0.0410
Epoch 31/50
43/43 [=====] - 464s 11s/step - loss: 0.0410
Epoch 32/50
43/43 [=====] - 476s 11s/step - loss: 0.0410
Epoch 33/50
```

```
43/43 [=====] - 463s 11s/step - loss: 0.0410
Epoch 34/50
43/43 [=====] - 478s 11s/step - loss: 0.0410
Epoch 35/50
43/43 [=====] - 467s 11s/step - loss: 0.0410
Epoch 36/50
43/43 [=====] - 473s 11s/step - loss: 0.0410
Epoch 37/50
43/43 [=====] - 471s 11s/step - loss: 0.0410
Epoch 38/50
43/43 [=====] - 468s 11s/step - loss: 0.0410
Epoch 39/50
43/43 [=====] - 476s 11s/step - loss: 0.0410
Epoch 40/50
43/43 [=====] - 468s 11s/step - loss: 0.0410
Epoch 41/50
43/43 [=====] - 475s 11s/step - loss: 0.0410
Epoch 42/50
43/43 [=====] - 469s 11s/step - loss: 0.0410
Epoch 43/50
43/43 [=====] - 475s 11s/step - loss: 0.0410
Epoch 44/50
43/43 [=====] - 480s 11s/step - loss: 0.0410
Epoch 45/50
43/43 [=====] - 471s 11s/step - loss: 0.0410
Epoch 46/50
43/43 [=====] - 485s 11s/step - loss: 0.0410
Epoch 47/50
43/43 [=====] - 471s 11s/step - loss: 0.0410
Epoch 48/50
43/43 [=====] - 484s 11s/step - loss: 0.0410
Epoch 49/50
43/43 [=====] - 479s 11s/step - loss: 0.0410
Epoch 50/50
43/43 [=====] - 478s 11s/step - loss: 0.0410
got model
(200, 227, 227, 1)
```





In [11]:

```

def plotROC(pr):
    y_pred = pr
    y_test = [1 for element in range(0, 200)]

    for i in TestVideoFile[Config.SINGLE_TEST_VIDEO_FILE]:
        y_test[i] = 0

    y_test = y_test[8:199] #testing with different removals to match number

    fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred)
    fnr = 1 - tpr
    auc = metrics.roc_auc_score(y_test, y_pred)

    eer_threshold = thresholds[np.nanargmin(np.absolute((fnr - fpr)))]
    eer = fpr[np.nanargmin(np.absolute((fnr - fpr)))]

    optimal = np.argmax(tpr - fpr)
    optimal_threshold = thresholds[optimal]

    #print("FPR: ", fpr)
    #print("TPR: ", tpr)
    #print("THRESHOLDS", thresholds)
    print("AUC: ", auc)
    print("EER: ", eer)
    print("EER THRESHOLD: ", eer_threshold)
    print("Optimal threshold value is:", optimal_threshold)

    plt.title('Receiver Operating Characteristic')
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % auc)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1], 'r--')
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()

    plt.plot(y_test)
    plt.title('Labels') #labels(flags, 0-1)
    plt.ylabel('GT')
    plt.xlabel('Frame')
    plt.show()

    return auc, eer

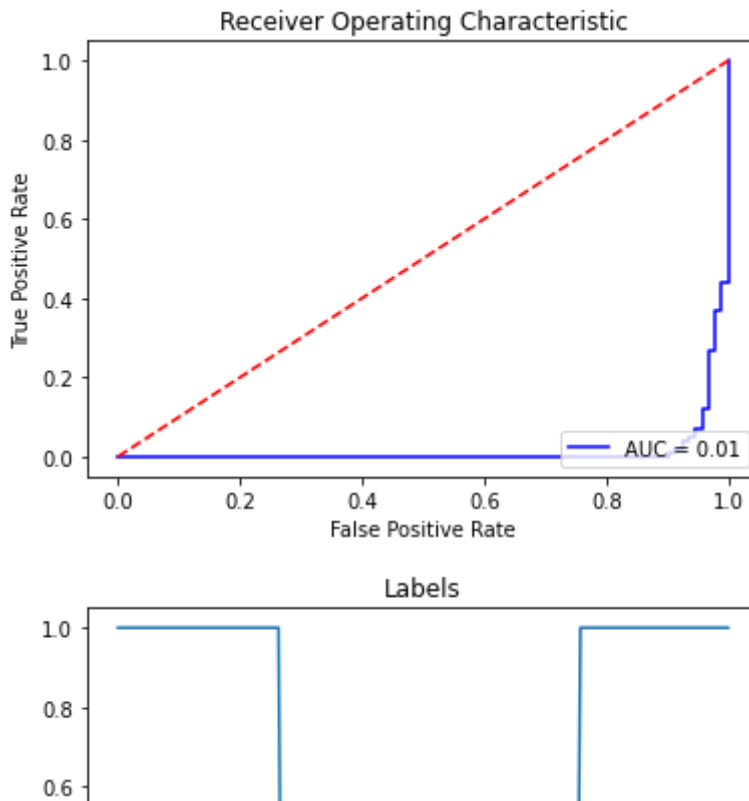
plotROC(pr)

```

```

AUC:  0.01492209787140662
EER:  0.946236559139785
EER THRESHOLD:  0.9835342593082625
Optimal threshold value is: 2.0

```



In [12]:

```

clips = []
# loop over the testing videos to get every single one
for f in sorted(listdir(Config.TEST_PATH)):
    if isdir(join(Config.TEST_PATH, f)):
        if not 'gt' in f:
            clips.append(join(Config.TEST_PATH, f))

scores = []

for i in range(len(clips)):
    if(i == 16): #skip clip 17 -> does not work
        continue

    Config.SINGLE_TEST_PATH = clips[i]
    Config.SINGLE_TEST_VIDEO_FILE = i+1

    print("PATH: ", Config.SINGLE_TEST_PATH)
    print("GT: ", Config.SINGLE_TEST_VIDEO_FILE)

    pr = evaluate()
    scores.append(plotROC(pr))

mean = np.mean(scores, axis=0) #calculating the mean value of all AUCs and EERs
#print(scores)
print("AUC: ", mean[0])
print("EER: ", mean[1])

```

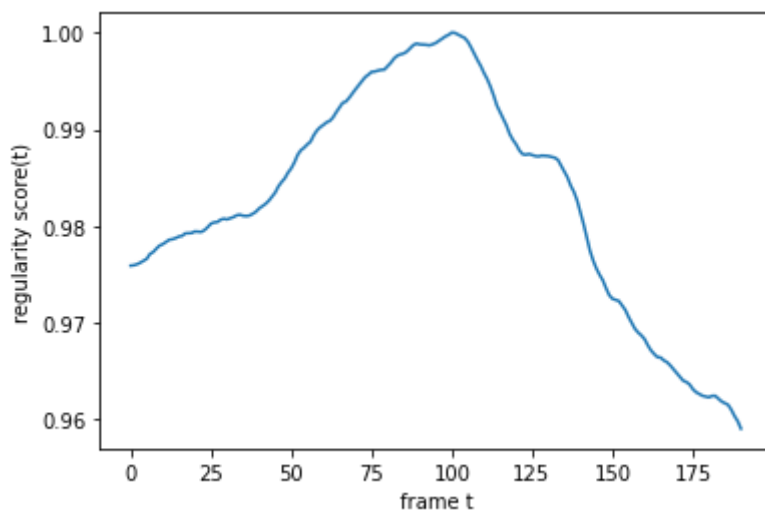
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test001

GT: 1

got model

(200, 227, 227, 1)

got data

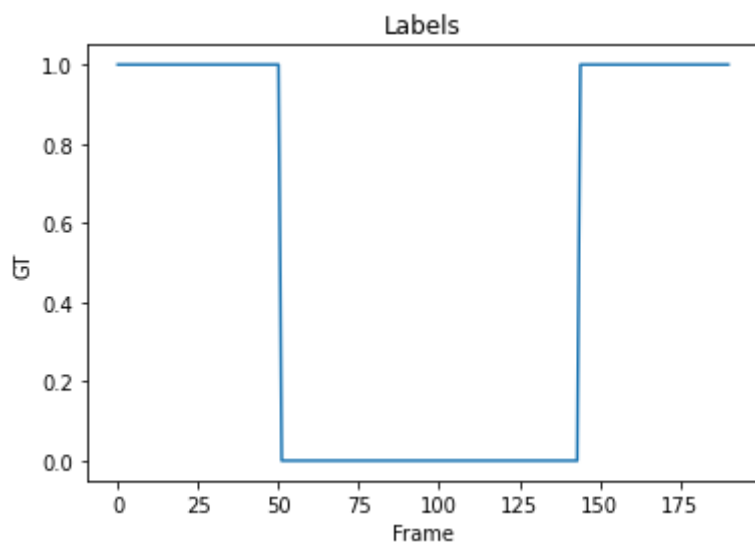
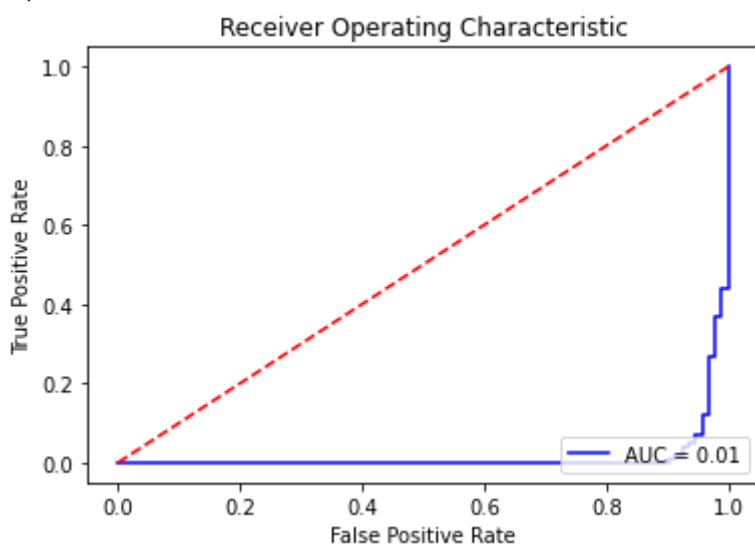


AUC: 0.01492209787140662

EER: 0.946236559139785

EER THRESHOLD: 0.9835342593082625

Optimal threshold value is: 2.0



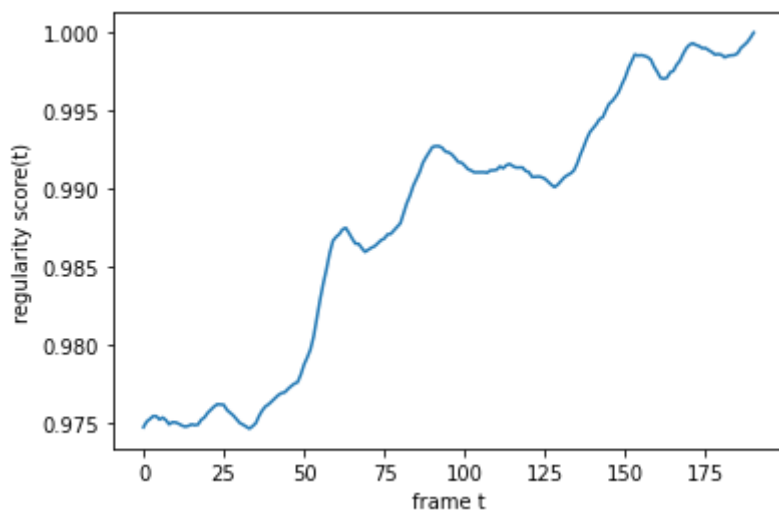
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test002

GT: 2

got model

(200, 227, 227, 1)

got data

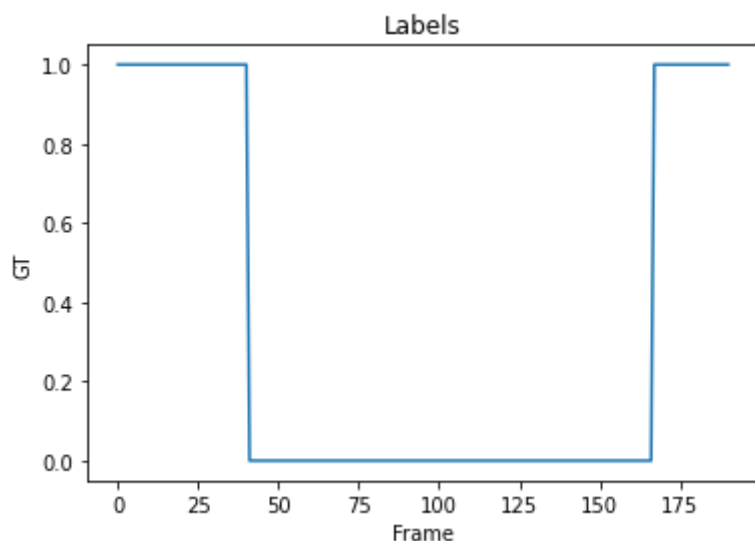
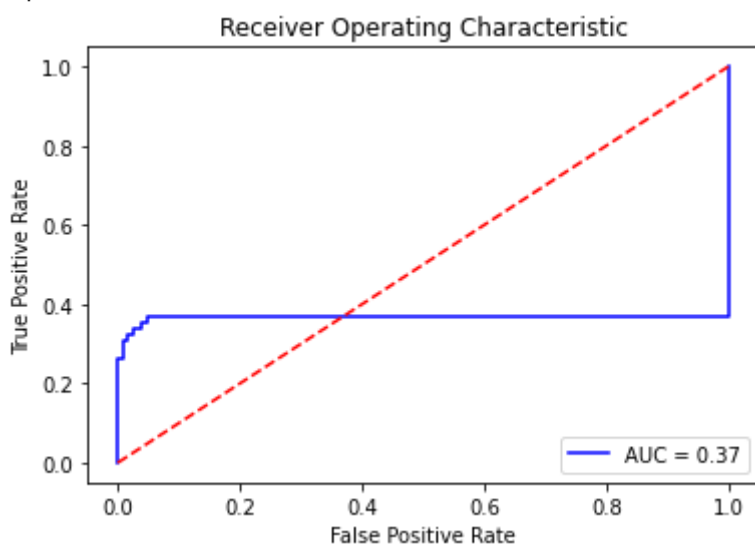


AUC: 0.36691086691086694

EER: 1.0

EER THRESHOLD: 0.9765661355120089

Optimal threshold value is: 0.9981894548688542



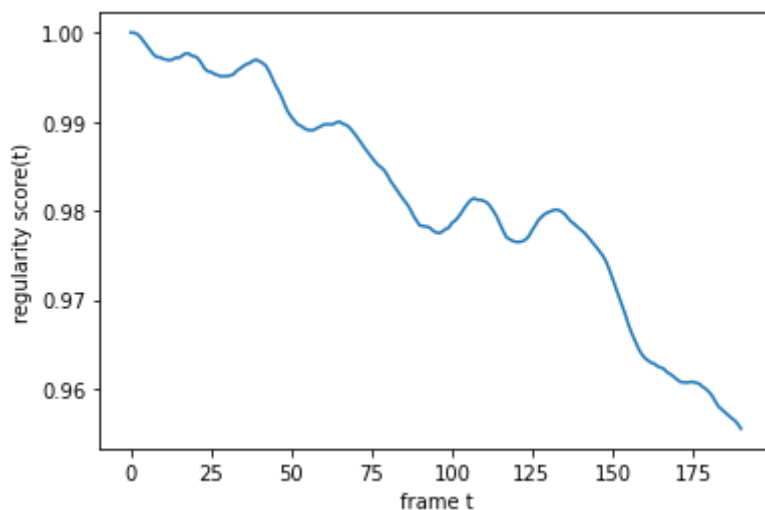
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test003

GT: 3

got model

(200, 227, 227, 1)

got data

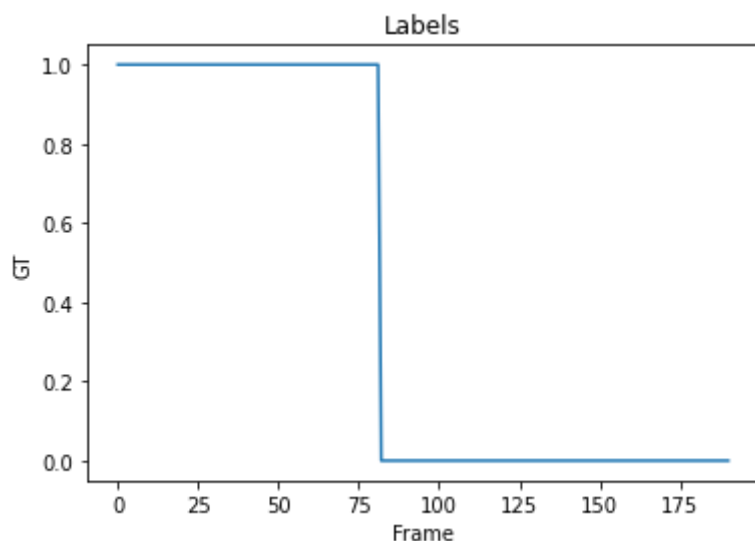
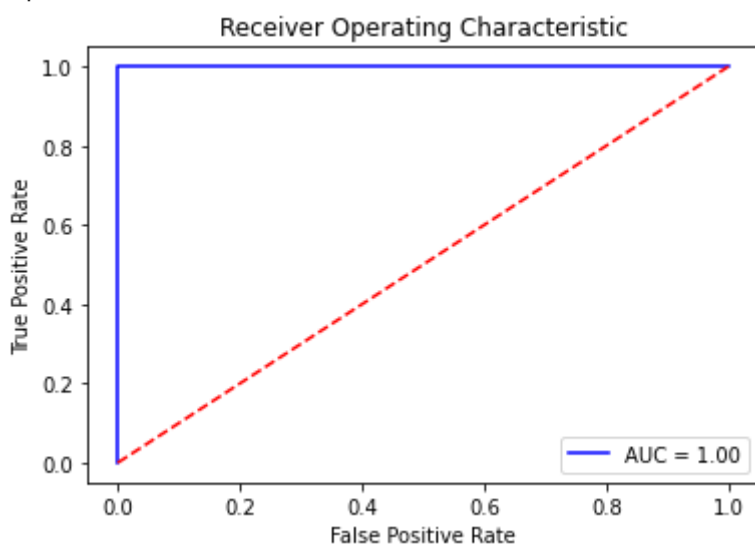


AUC: 1.0

EER: 0.0

EER THRESHOLD: 0.9832831117613453

Optimal threshold value is: 0.9832831117613453



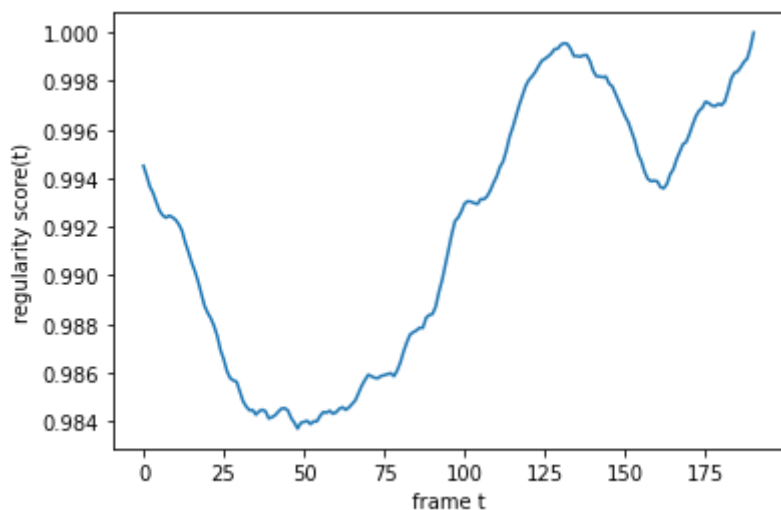
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test004

GT: 4

got model

(200, 227, 227, 1)

got data

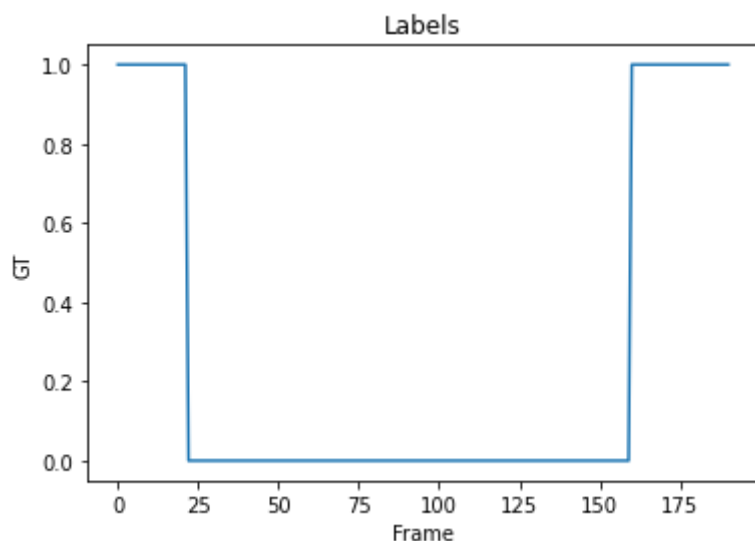
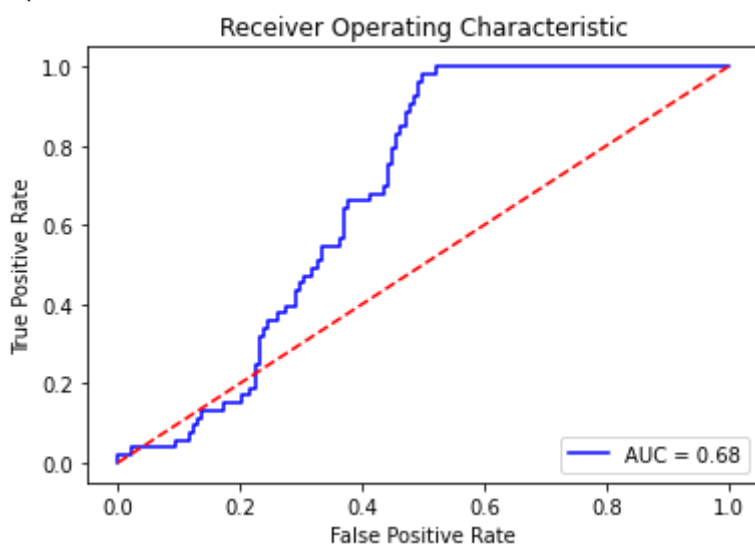


AUC: 0.6808859721082855

EER: 0.3695652173913043

EER THRESHOLD: 0.9935879839434365

Optimal threshold value is: 0.9884600386638904



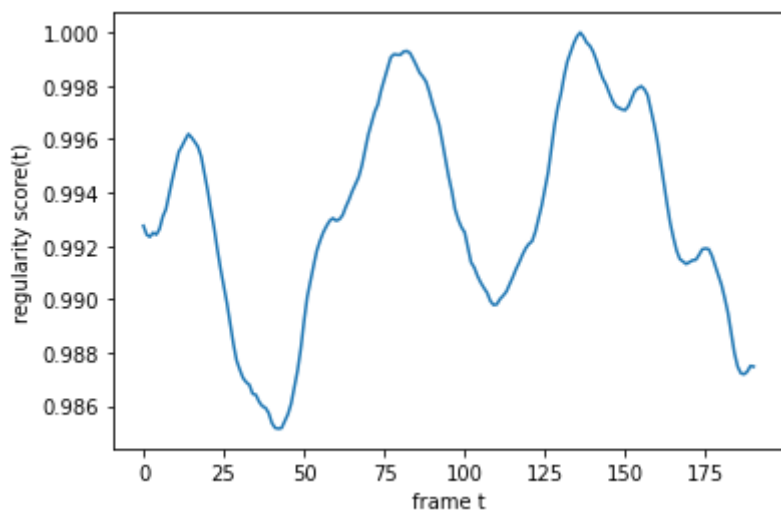
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test005

GT: 5

got model

(200, 227, 227, 1)

got data

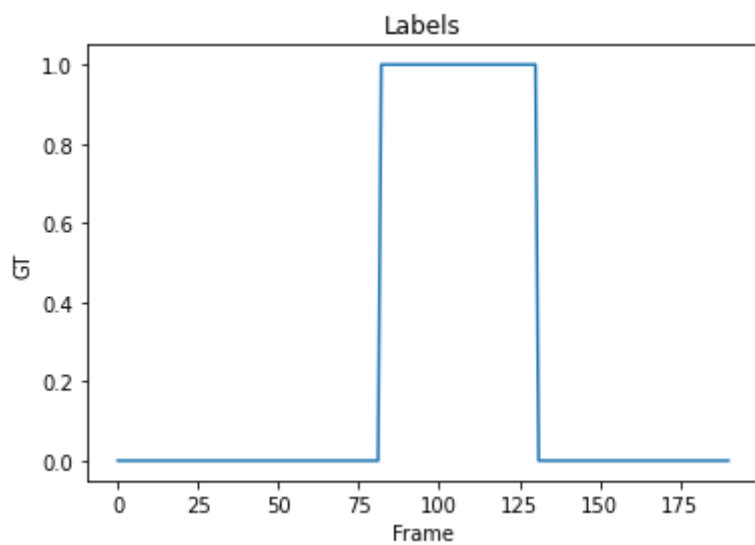
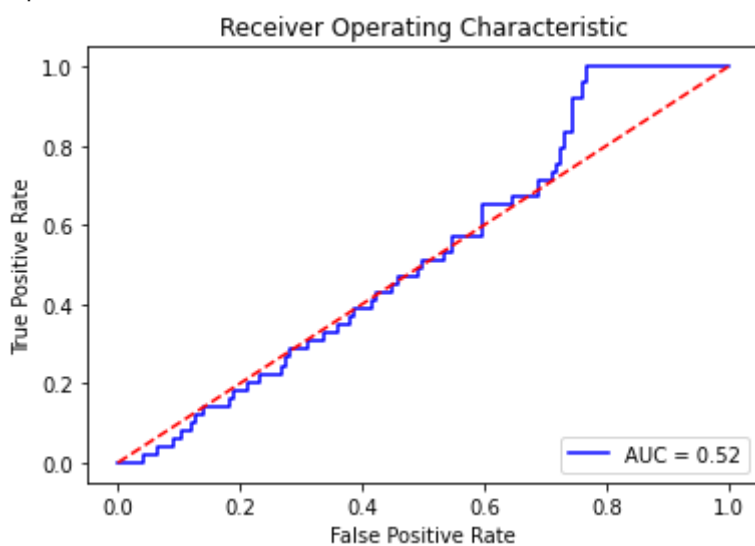


AUC: 0.524719747053751

EER: 0.5

EER THRESHOLD: 0.992992553386964

Optimal threshold value is: 0.9897817352494181



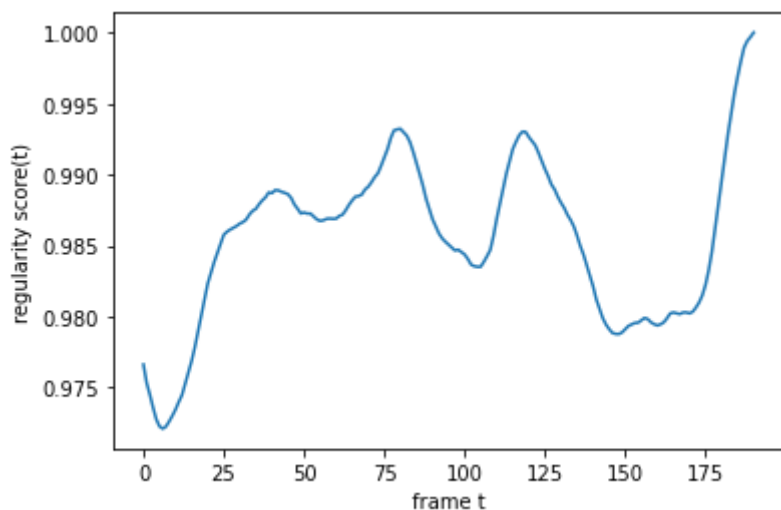
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test006

GT: 6

got model

(200, 227, 227, 1)

got data

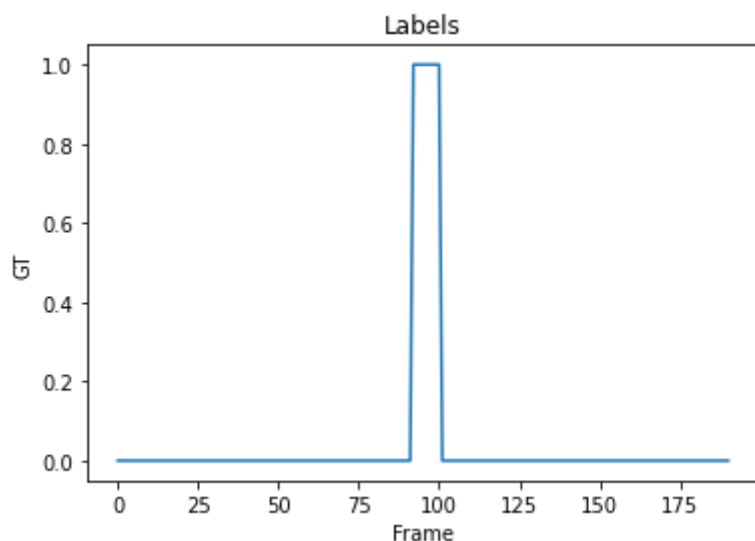
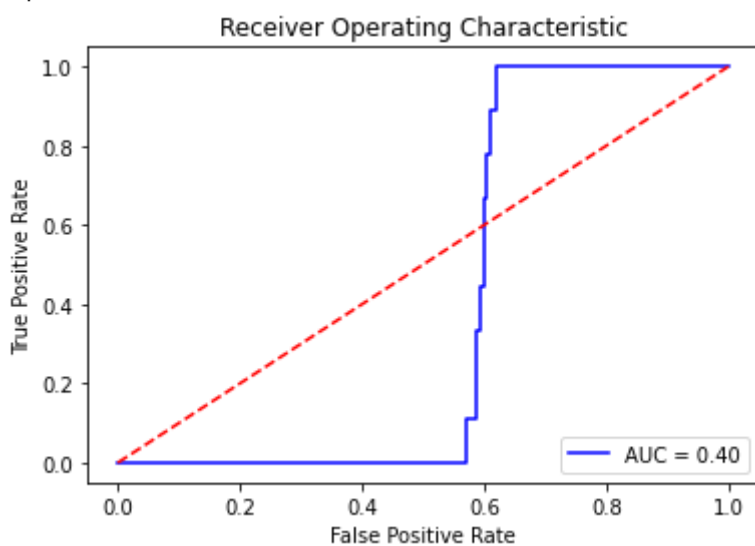


AUC: 0.40293040293040294

EER: 0.5934065934065934

EER THRESHOLD: 0.9850714971400839

Optimal threshold value is: 0.984377318730777



PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test007

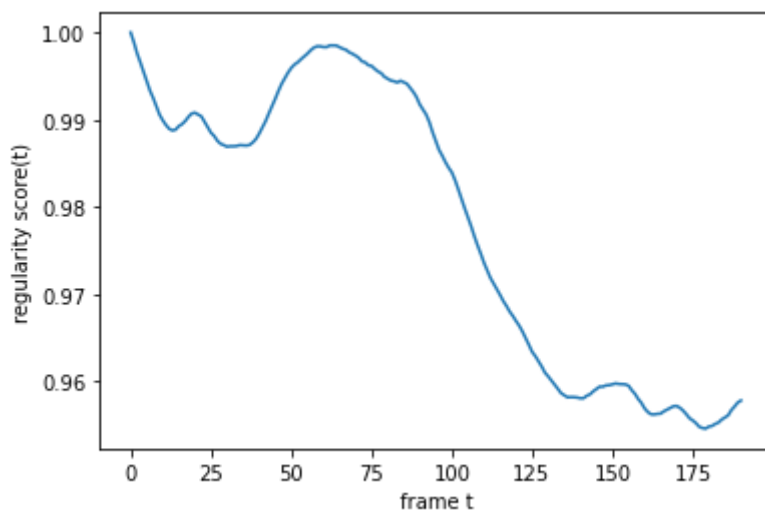
GT: 7

got model

(200, 227, 227, 1)

got data



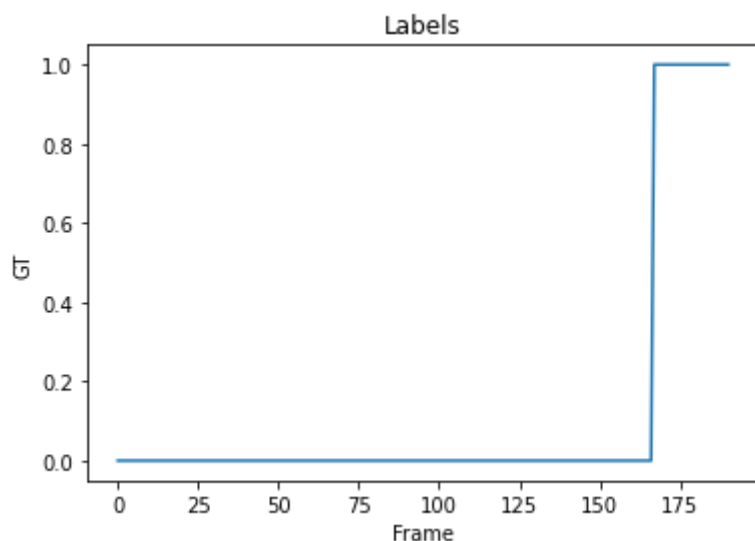
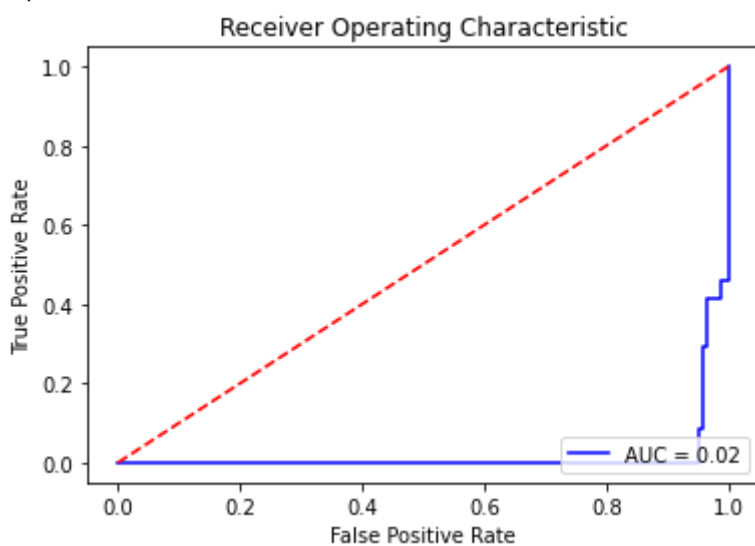


AUC: 0.01771457085828343

EER: 0.9520958083832335

EER THRESHOLD: 0.9575469374729314

Optimal threshold value is: 2.0



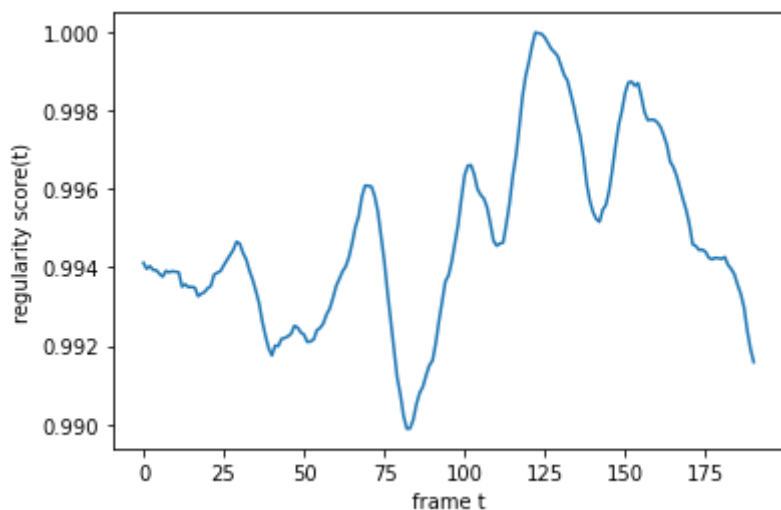
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test008

GT: 8

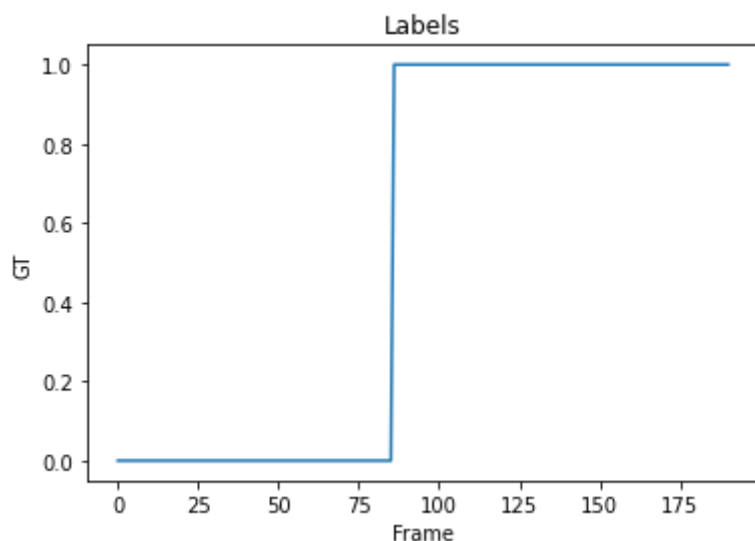
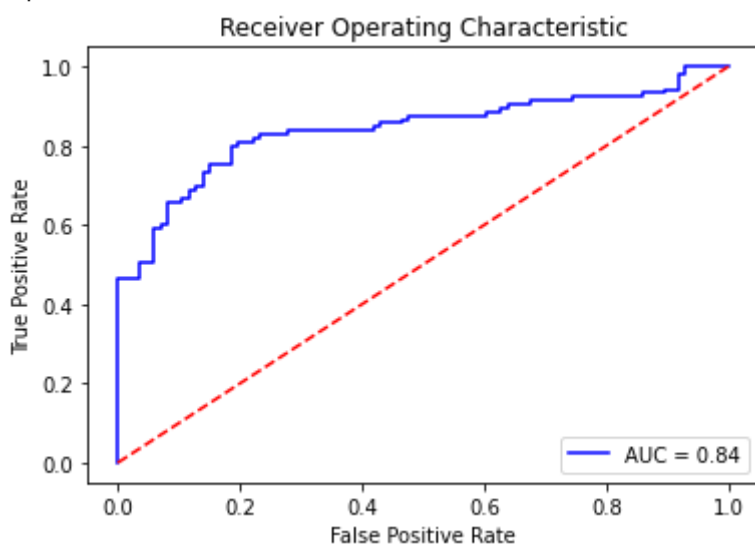
got model

(200, 227, 227, 1)

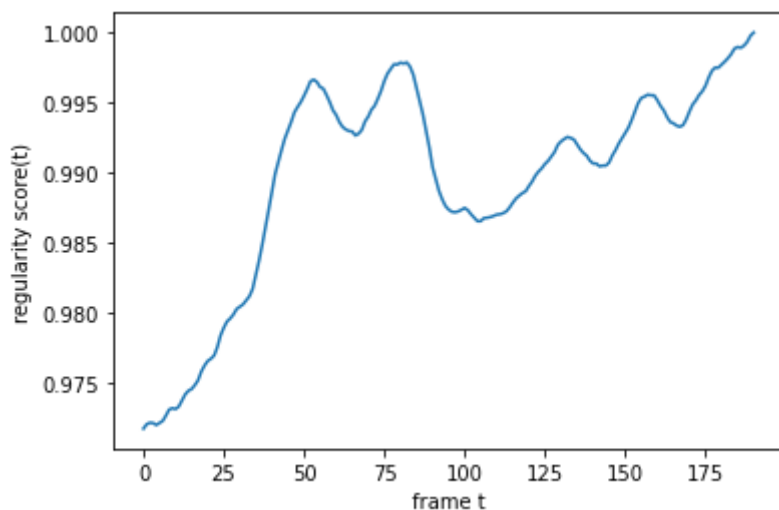
got data



AUC: 0.8401993355481728  
EER: 0.19767441860465115  
EER THRESHOLD: 0.9942065413785959  
Optimal threshold value is: 0.9942228813400523



PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test009  
GT: 9  
got model  
(200, 227, 227, 1)  
got data

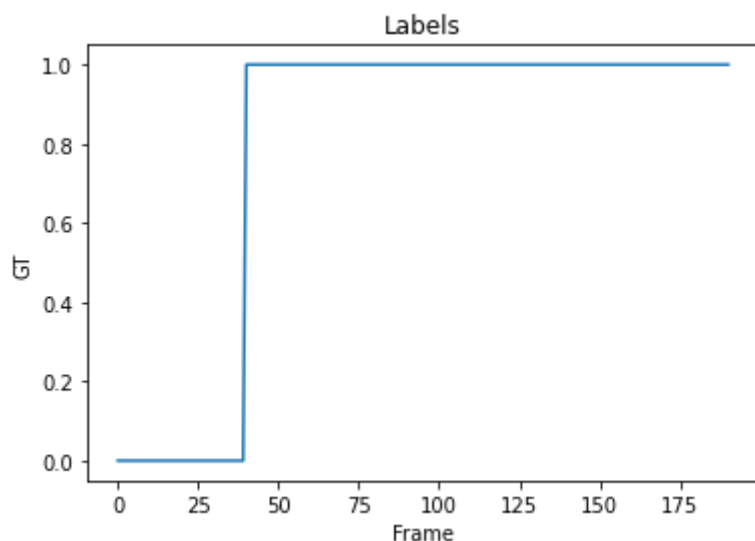
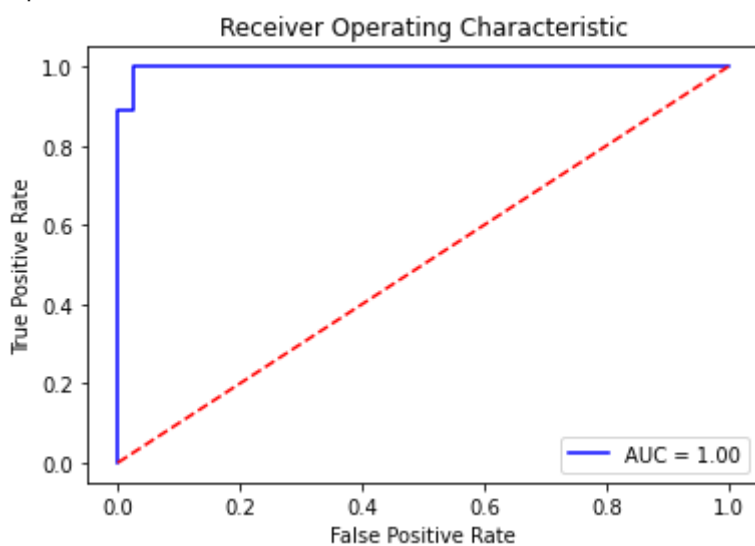


AUC: 0.9971854304635761

EER: 0.025

EER THRESHOLD: 0.9865614367290209

Optimal threshold value is: 0.9865614367290209



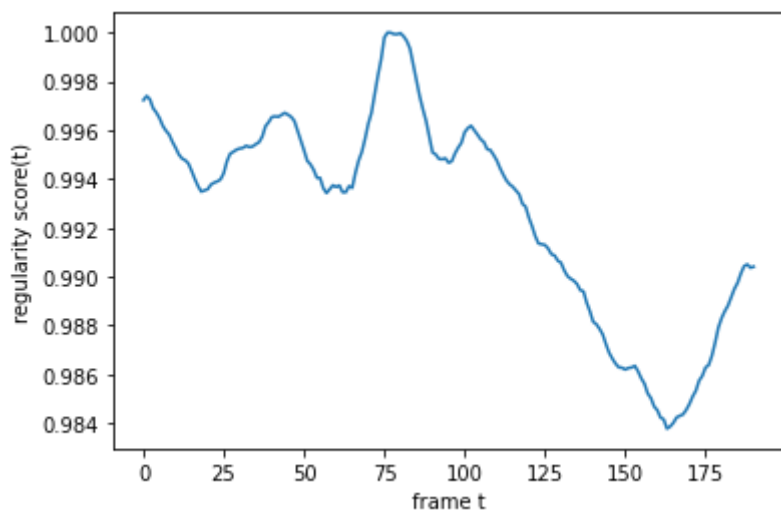
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test010

GT: 10

got model

(200, 227, 227, 1)

got data

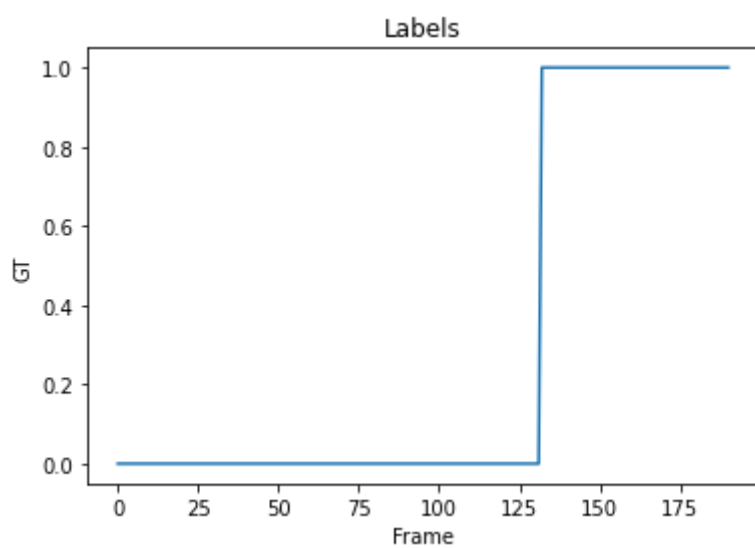
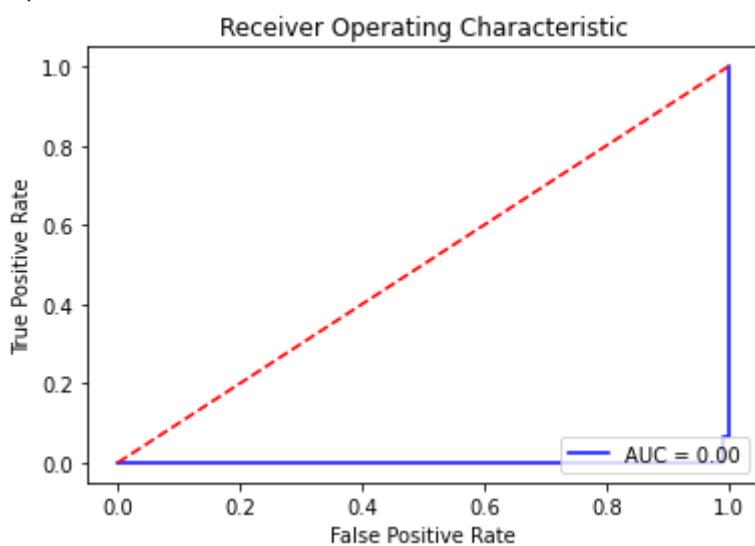


AUC: 0.0005136106831022081

EER: 0.9924242424242424

EER THRESHOLD: 0.9905735379262769

Optimal threshold value is: 2.0



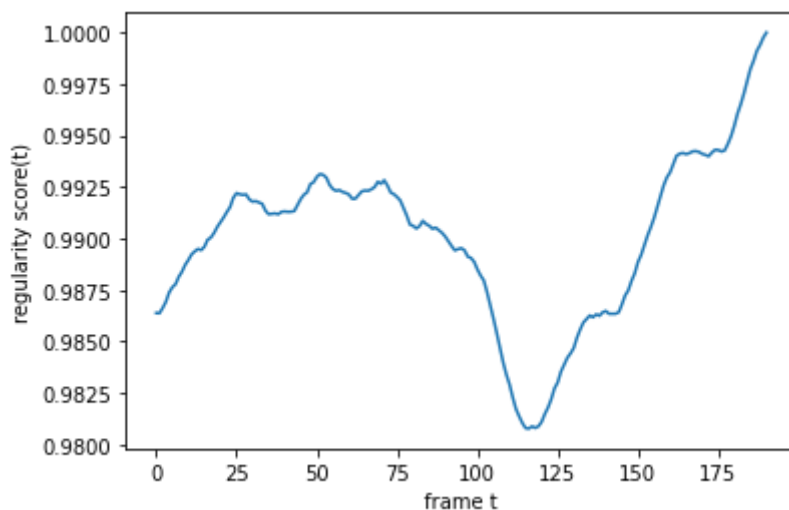
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test011

GT: 11

got model

(200, 227, 227, 1)

got data

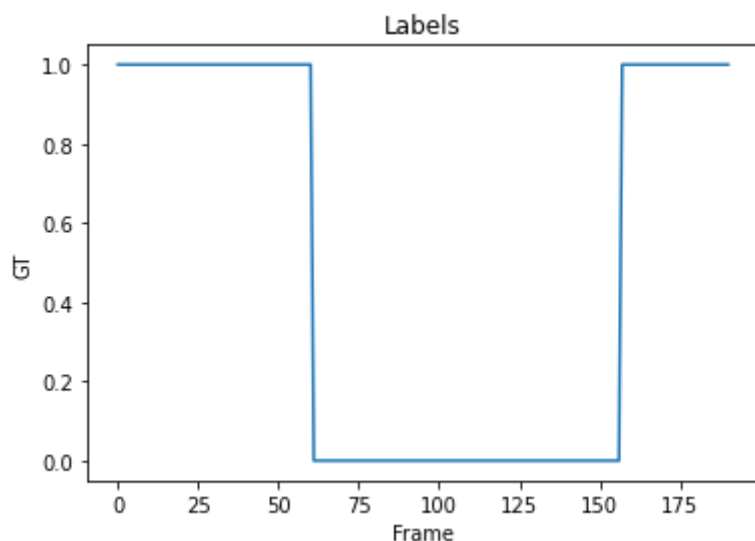
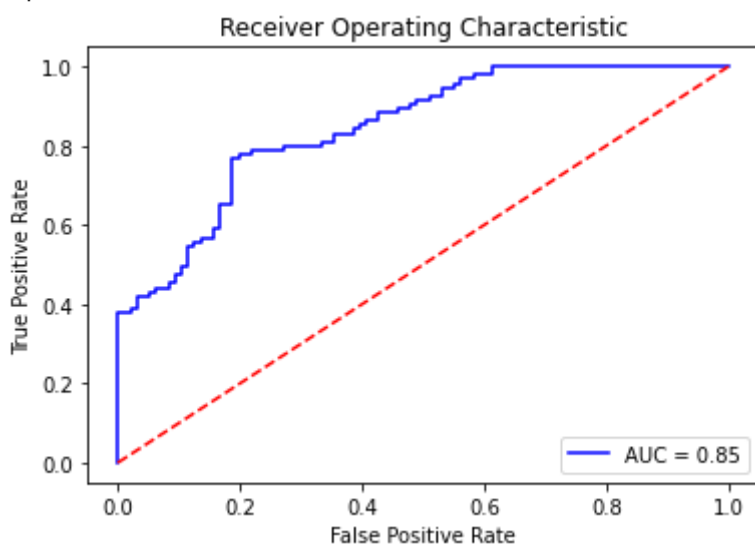


AUC: 0.8461622807017544

EER: 0.21875

EER THRESHOLD: 0.9908593848831139

Optimal threshold value is: 0.9910252394932282



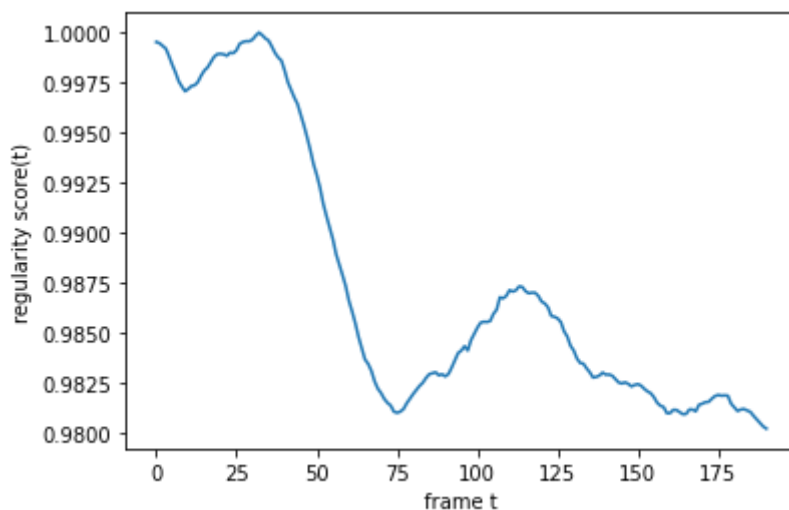
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test012

GT: 12

got model

(200, 227, 227, 1)

got data

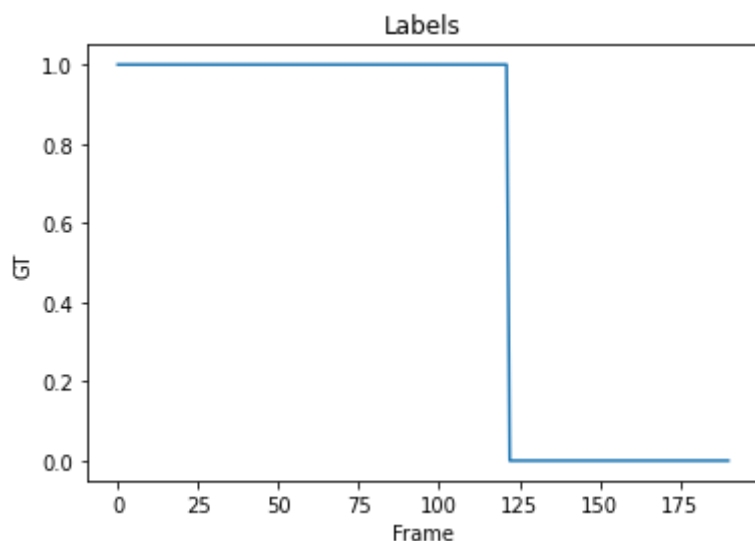
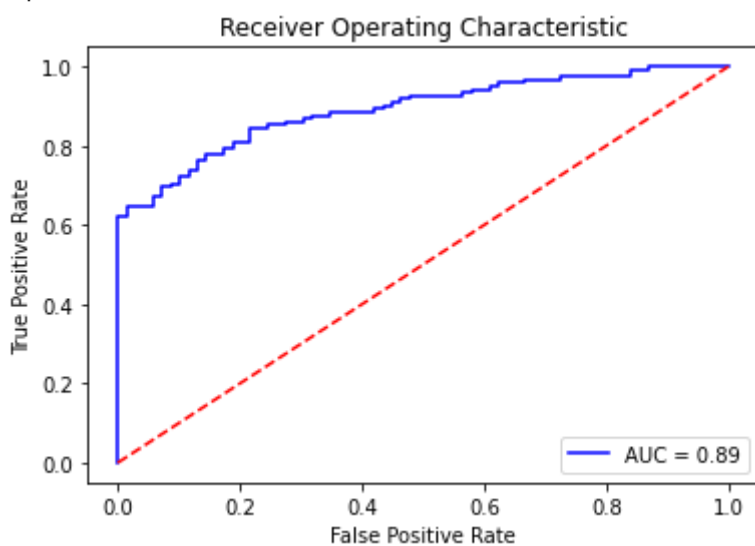


AUC: 0.8910667617011166

EER: 0.18840579710144928

EER THRESHOLD: 0.9830369514753164

Optimal threshold value is: 0.9836363992900877



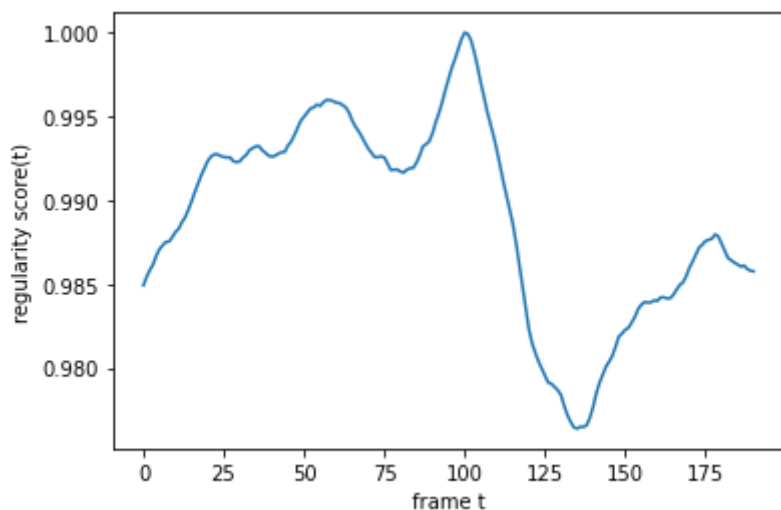
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test013

GT: 13

got model

(200, 227, 227, 1)

got data

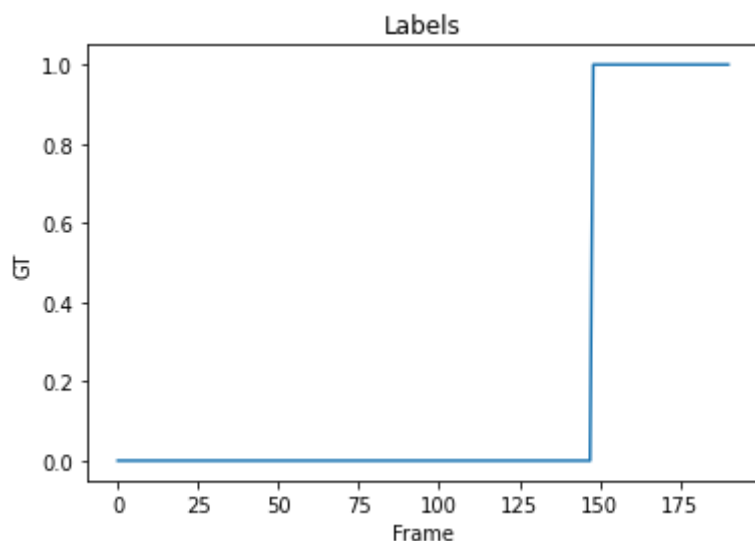
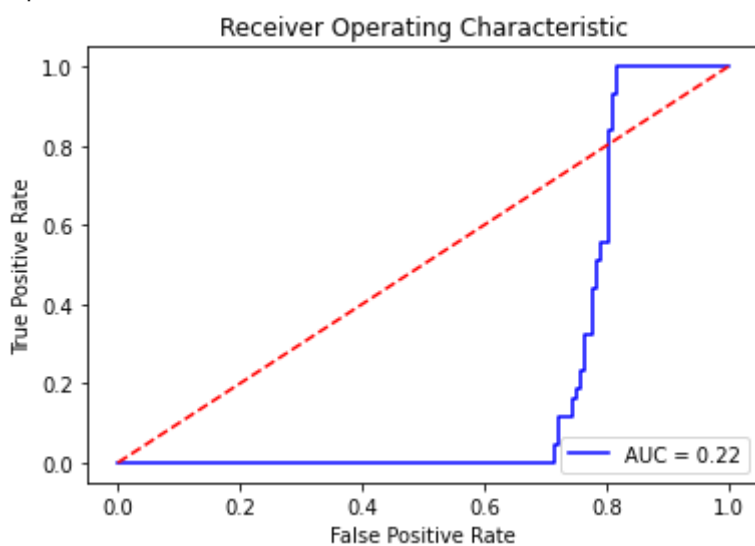


AUC: 0.21935889377749843

EER: 0.7635135135135135

EER THRESHOLD: 0.9866933152347778

Optimal threshold value is: 0.9818682193562874



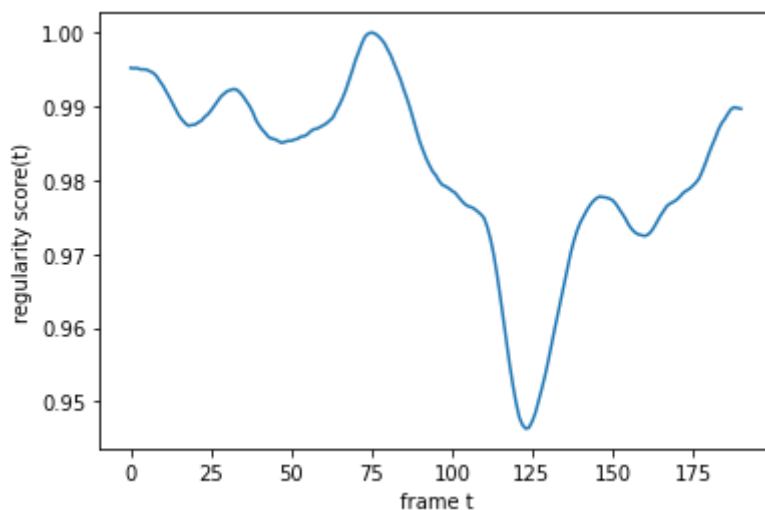
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test014

GT: 14

got model

(200, 227, 227, 1)

got data

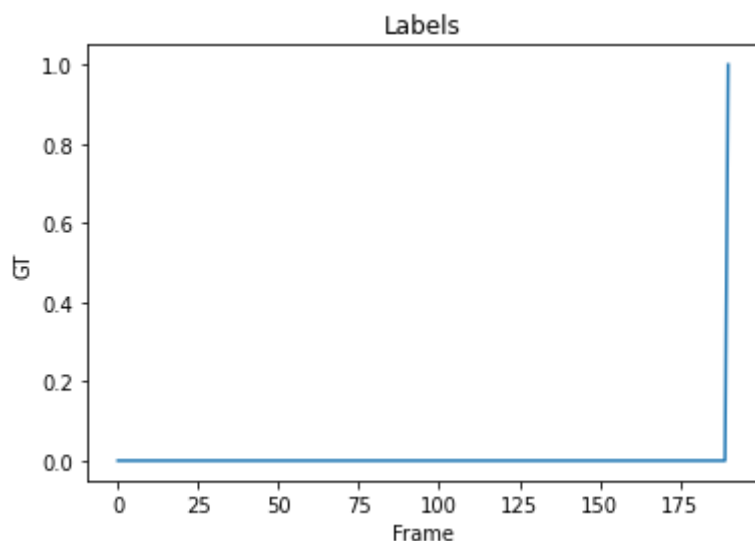
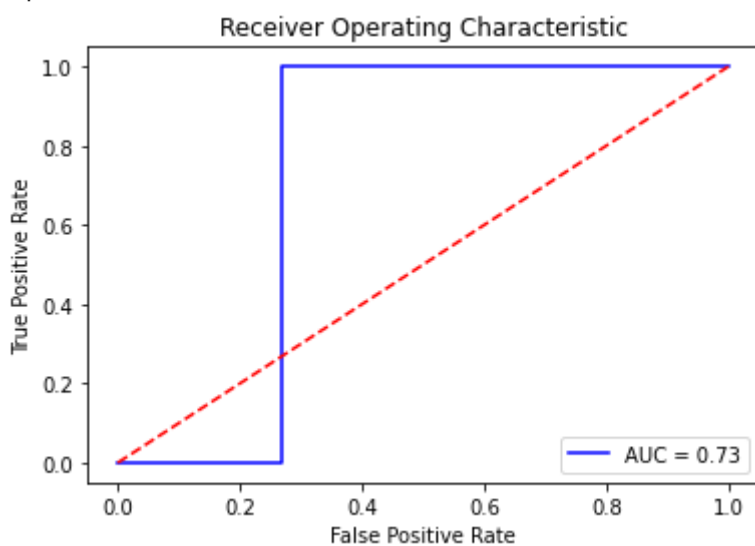


AUC: 0.7315789473684211

EER: 0.26842105263157895

EER THRESHOLD: 0.9896666297555512

Optimal threshold value is: 0.9896666297555512



PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test015

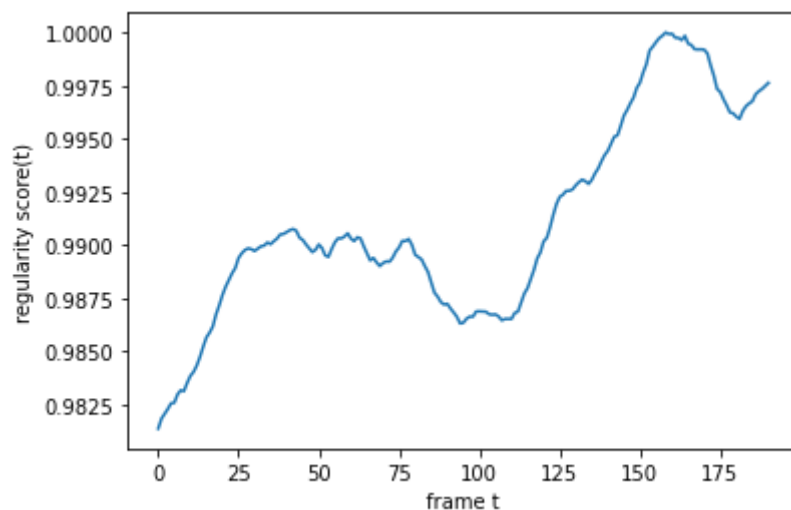
GT: 15

got model

(200, 227, 227, 1)

got data



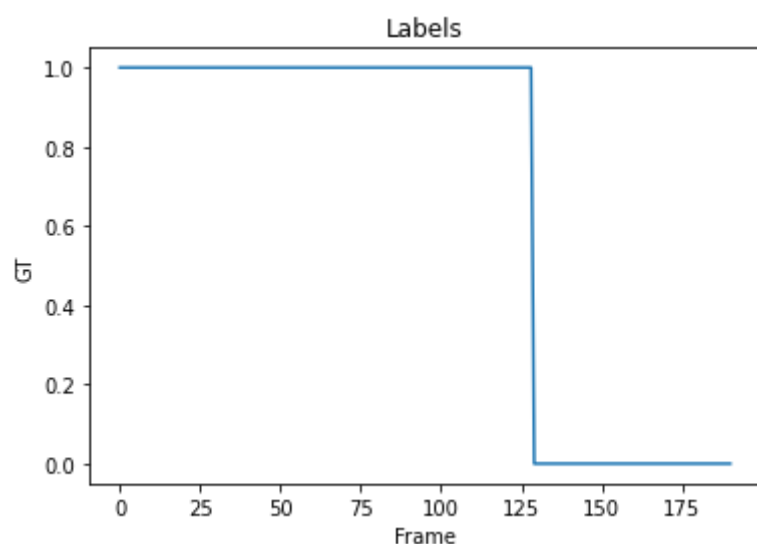
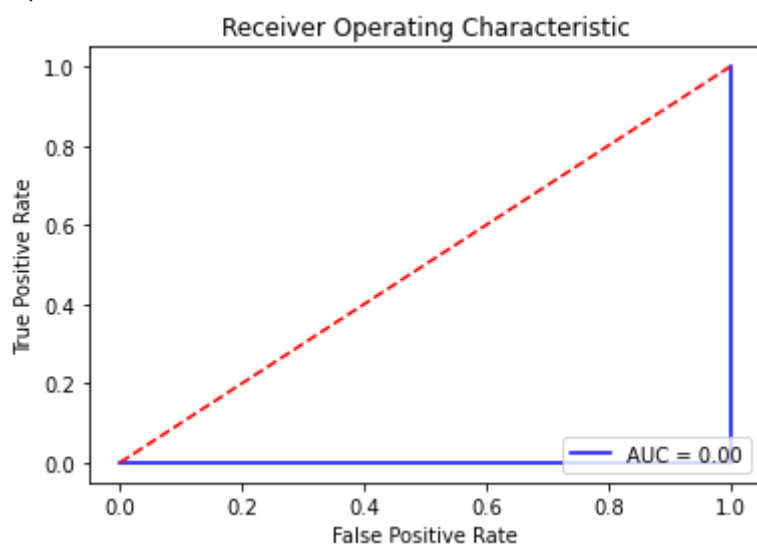


AUC: 0.0

EER: 1.0

EER THRESHOLD: 0.9926132559432149

Optimal threshold value is: 2.0



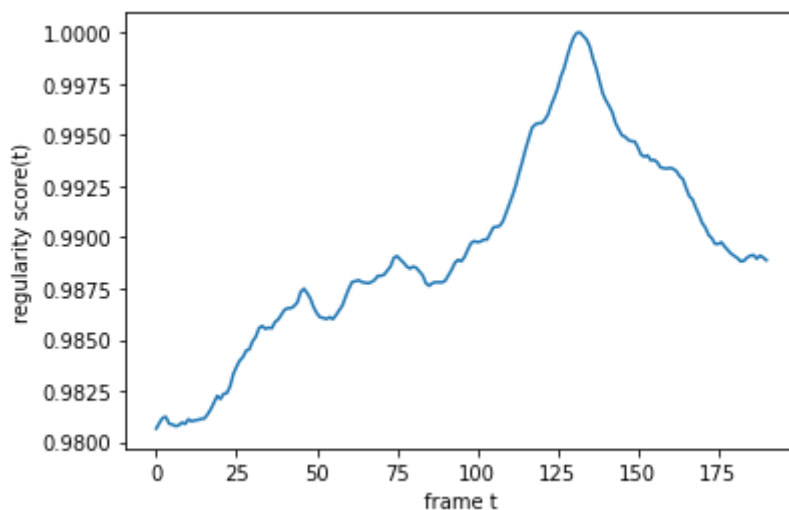
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test016

GT: 16

got model

(200, 227, 227, 1)

got data

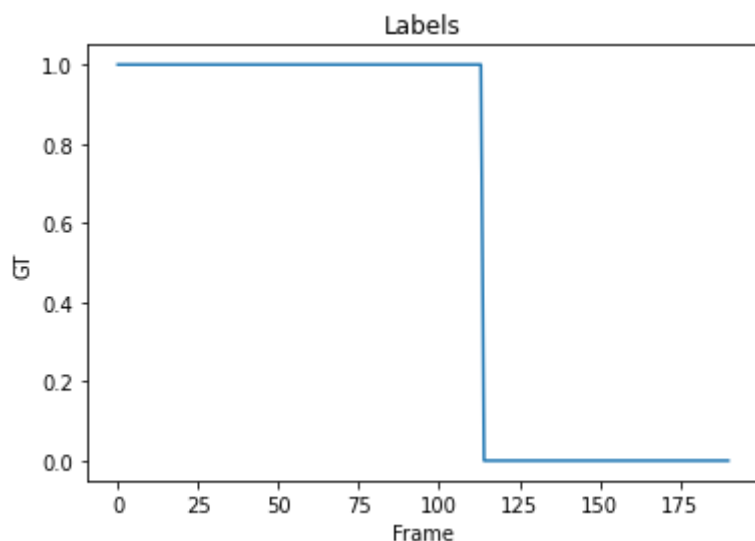
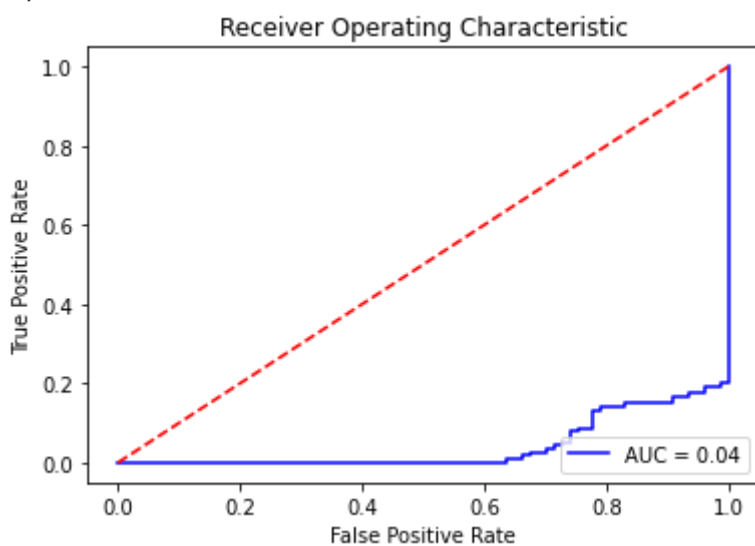


AUC: 0.04146730462519936

EER: 0.8311688311688312

EER THRESHOLD: 0.9893914217536139

Optimal threshold value is: 2.0



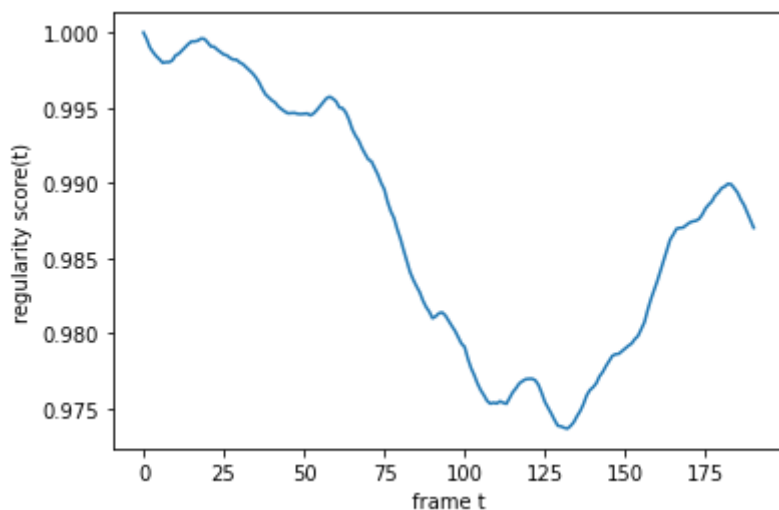
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test018

GT: 18

got model

(200, 227, 227, 1)

got data

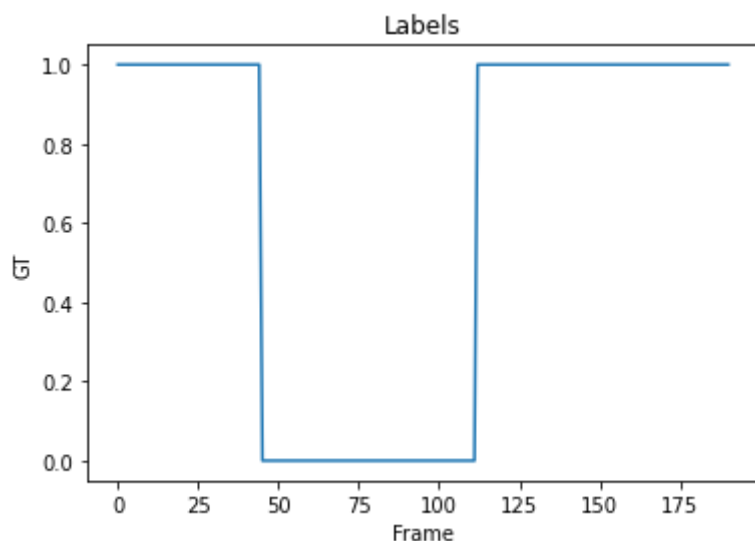
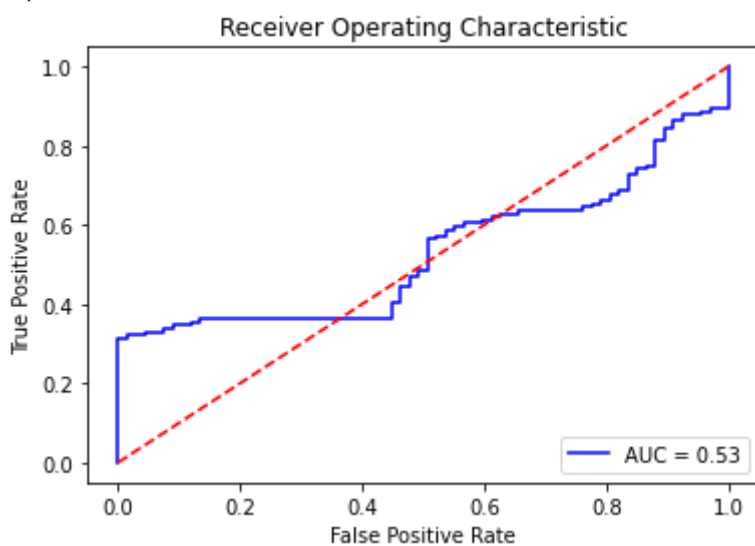


AUC: 0.5285267212325471

EER: 0.5074626865671642

EER THRESHOLD: 0.9876727939531719

Optimal threshold value is: 0.9958917549340376



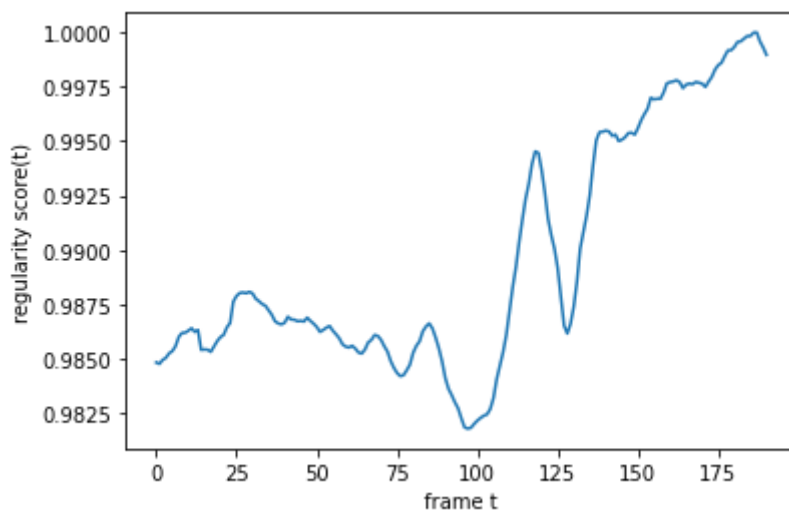
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test019

GT: 19

got model

(200, 227, 227, 1)

got data

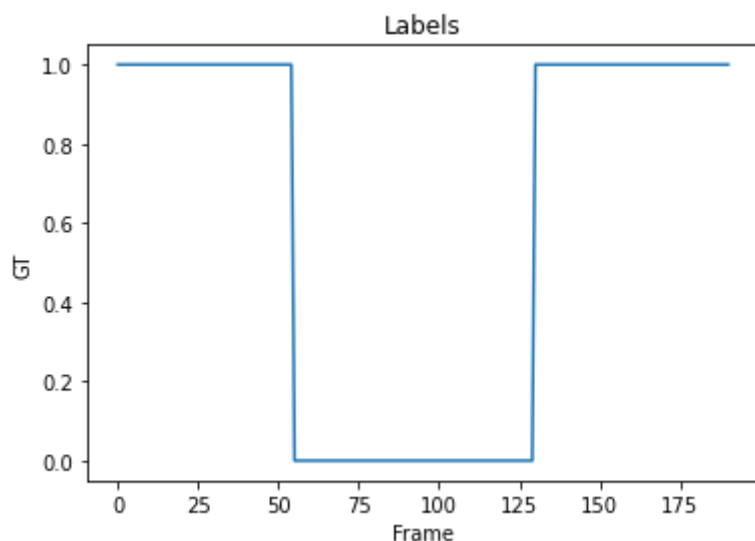
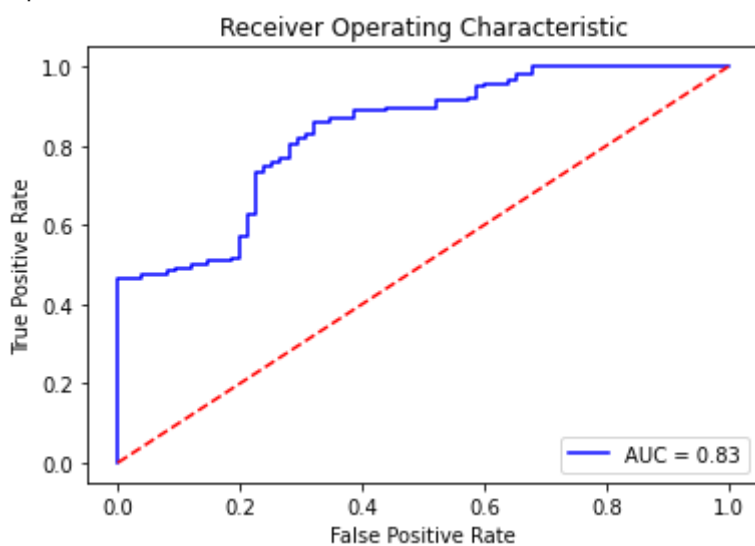


AUC: 0.834367816091954

EER: 0.25333333333333335

EER THRESHOLD: 0.9865940753007022

Optimal threshold value is: 0.9861698738756182



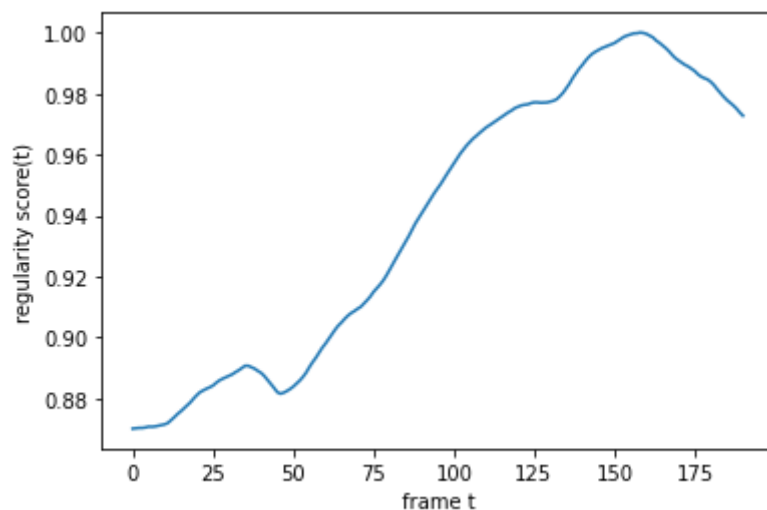
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test020

GT: 20

got model

(200, 227, 227, 1)

got data

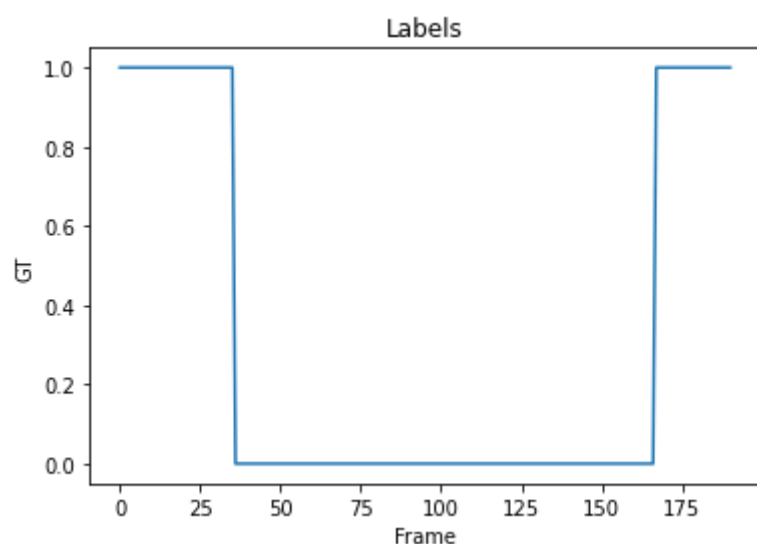
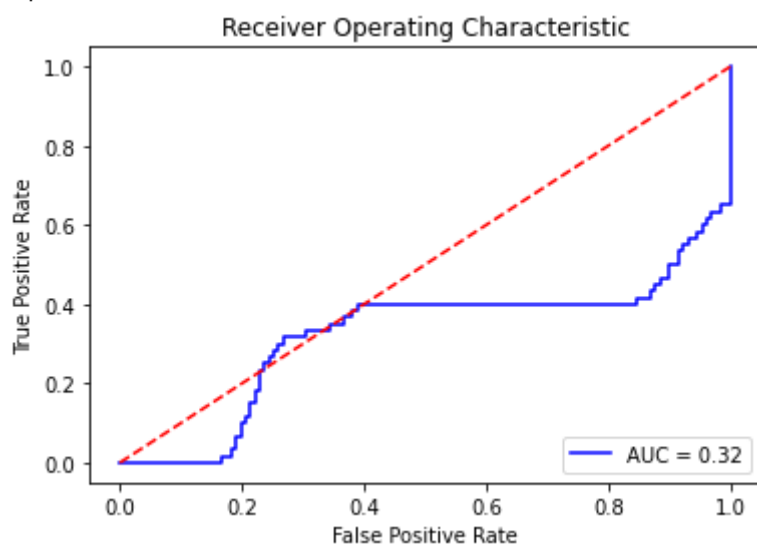


AUC: 0.3212468193384224

EER: 0.3893129770992366

EER THRESHOLD: 0.9727222086574338

Optimal threshold value is: 0.9778758299170154



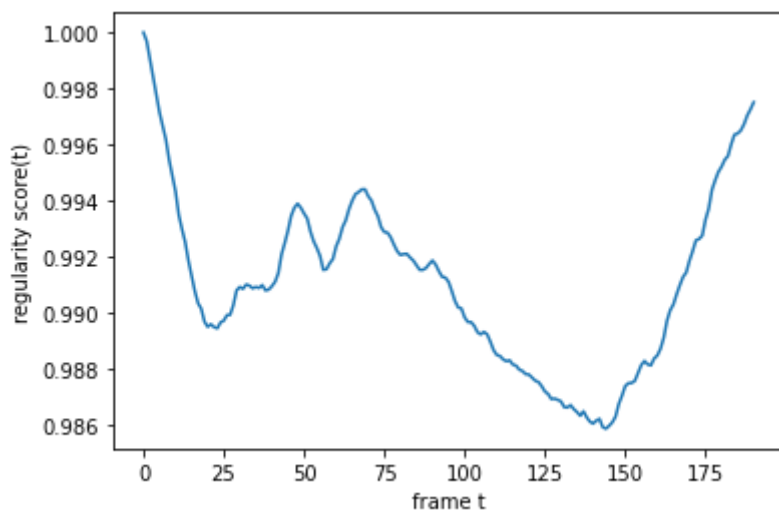
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test021

GT: 21

got model

(200, 227, 227, 1)

got data

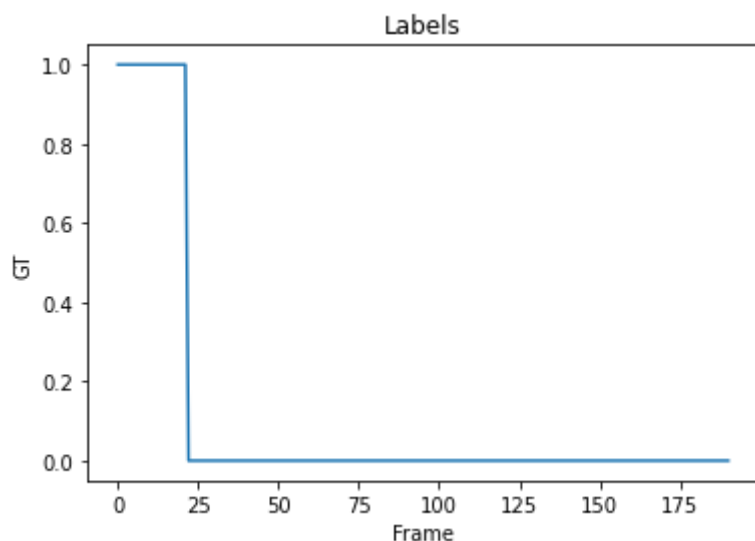
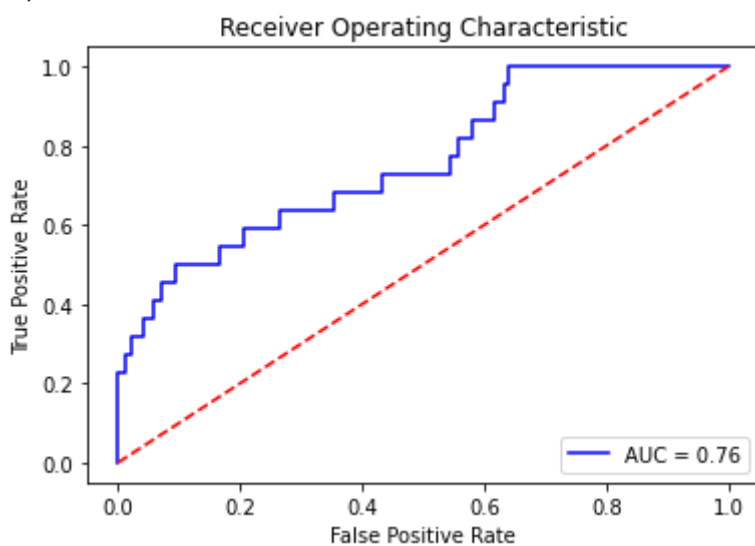


AUC: 0.7592791823561054

EER: 0.35502958579881655

EER THRESHOLD: 0.9918657316418088

Optimal threshold value is: 0.9943260540056195



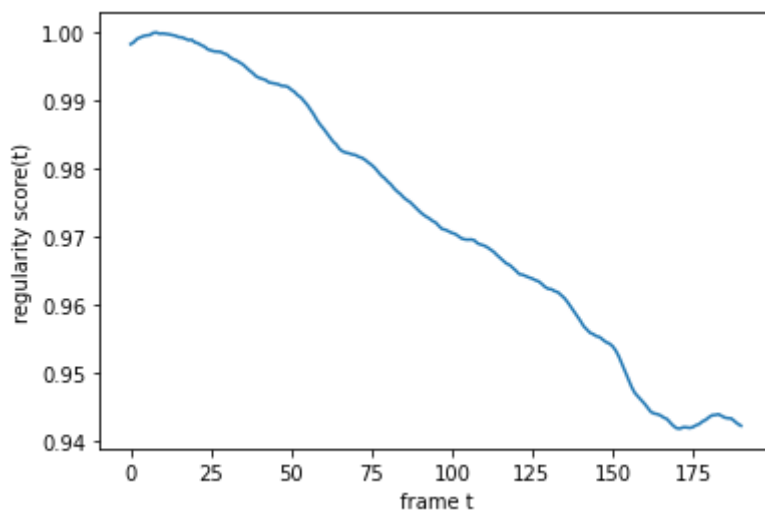
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test022

GT: 22

got model

(200, 227, 227, 1)

got data

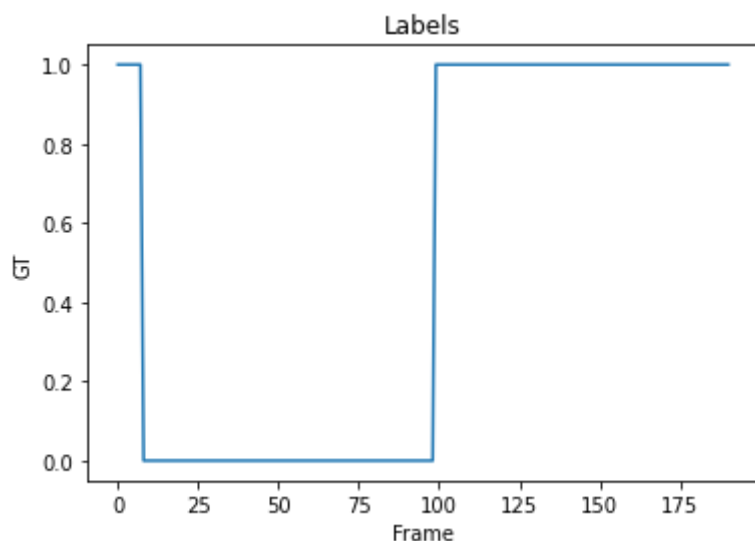
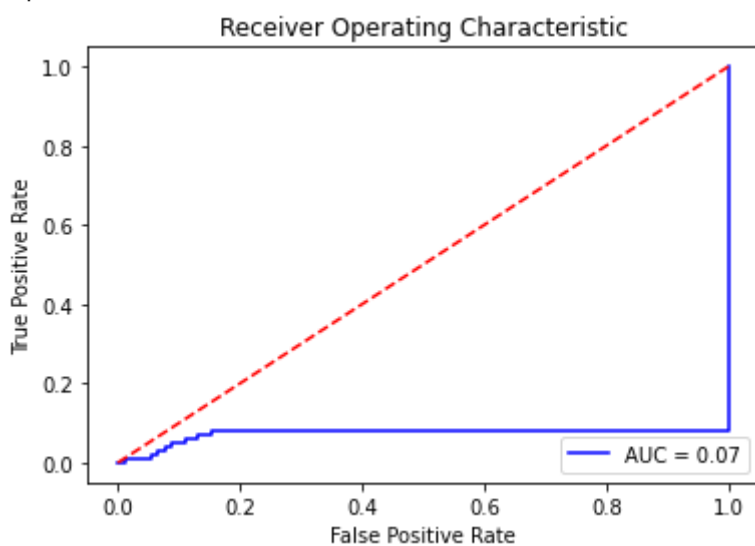


AUC: 0.07307692307692308

EER: 1.0

EER THRESHOLD: 0.9709700642441029

Optimal threshold value is: 2.0



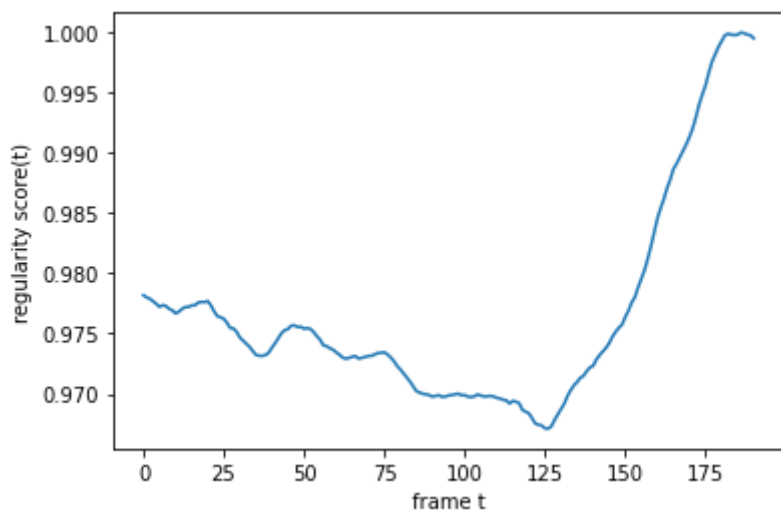
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test023

GT: 23

got model

(200, 227, 227, 1)

got data

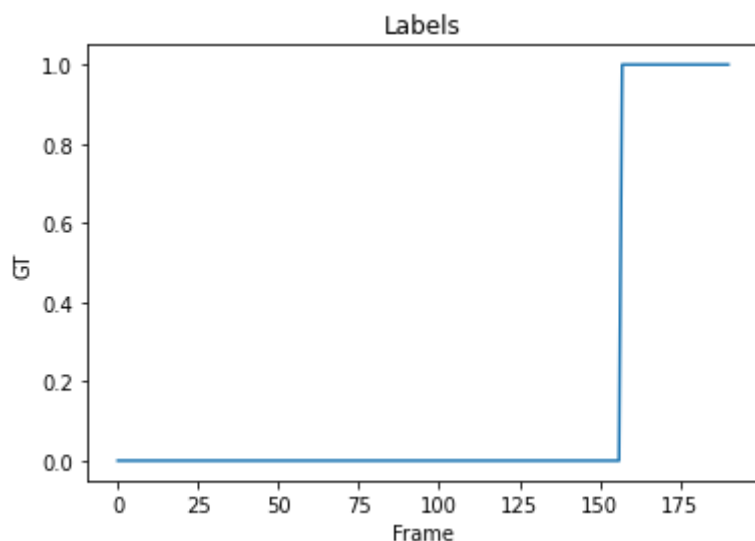
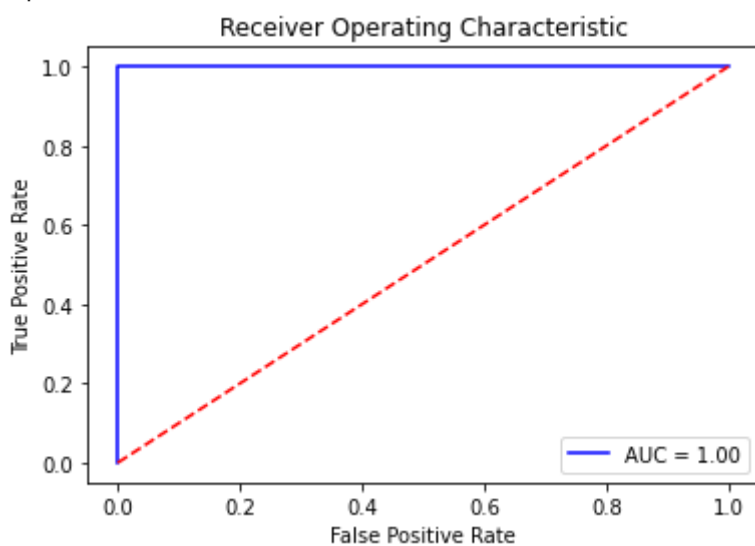


AUC: 1.0

EER: 0.0

EER THRESHOLD: 0.9811948858539867

Optimal threshold value is: 0.9811948858539867



PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test024

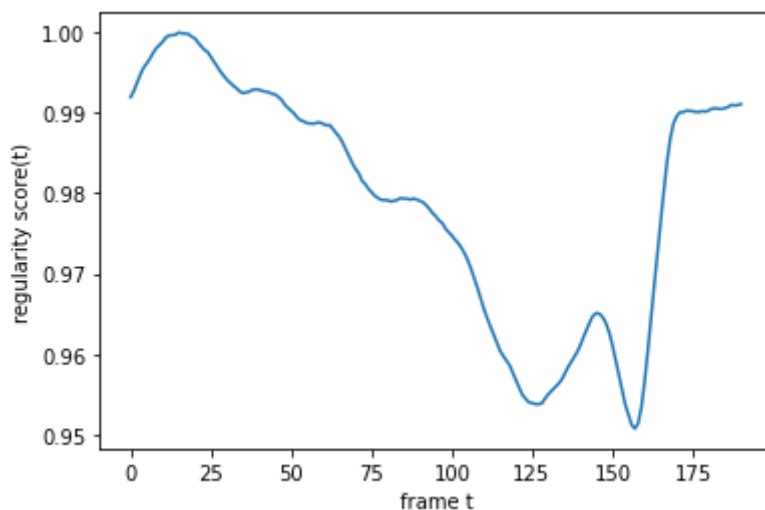
GT: 24

got model

(200, 227, 227, 1)

got data



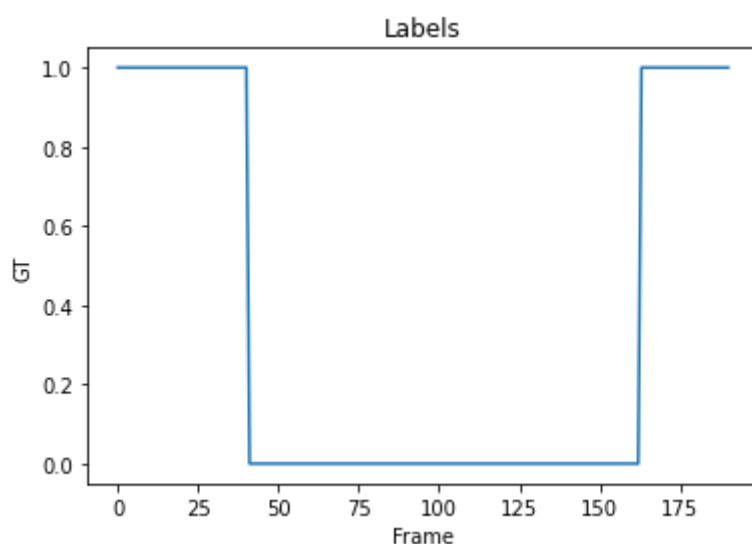
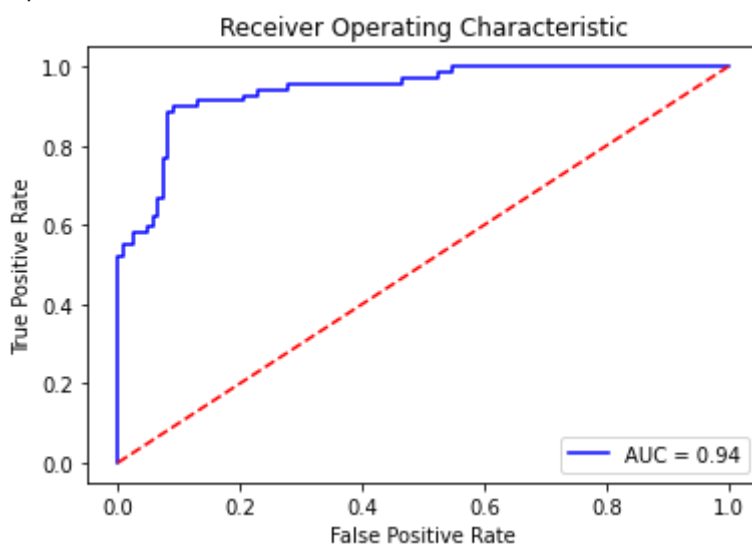


AUC: 0.9409598479448801

EER: 0.09016393442622951

EER THRESHOLD: 0.9895739094008191

Optimal threshold value is: 0.9895739094008191



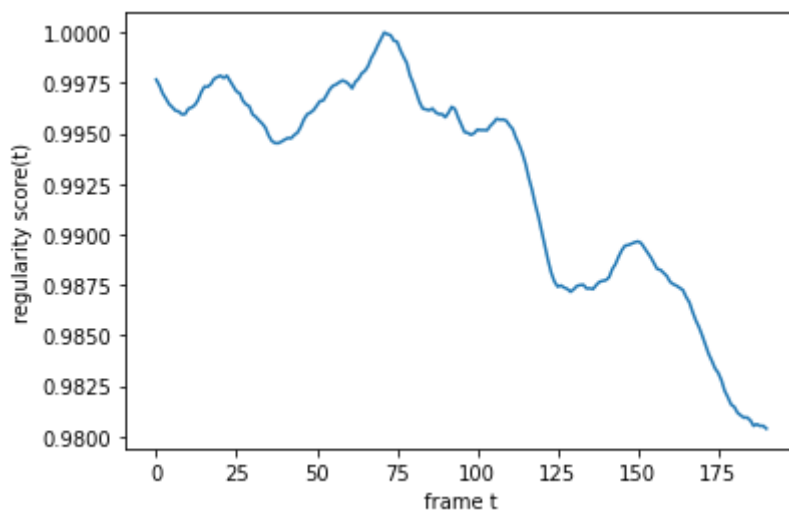
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test025

GT: 25

got model

(200, 227, 227, 1)

got data

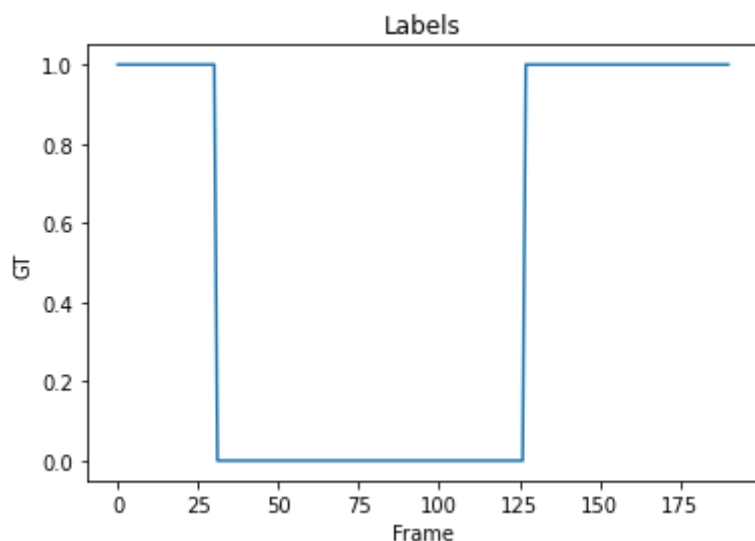
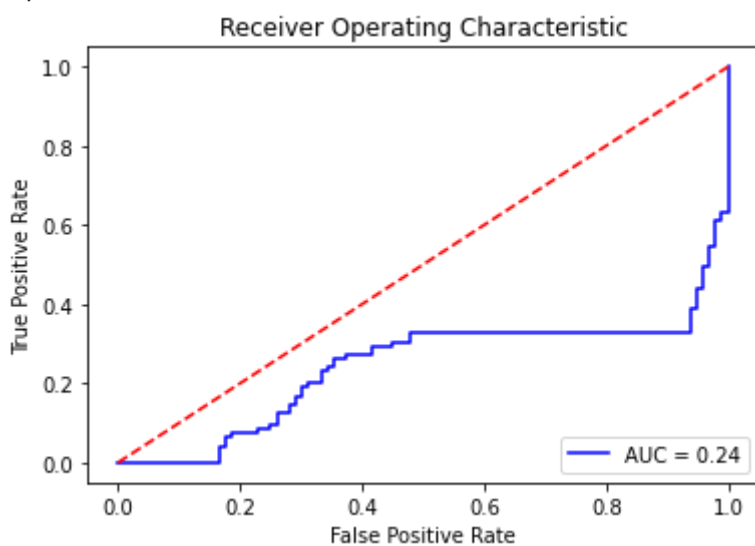


AUC: 0.24155701754385966

EER: 0.4791666666666667

EER THRESHOLD: 0.9959463228848823

Optimal threshold value is: 2.0



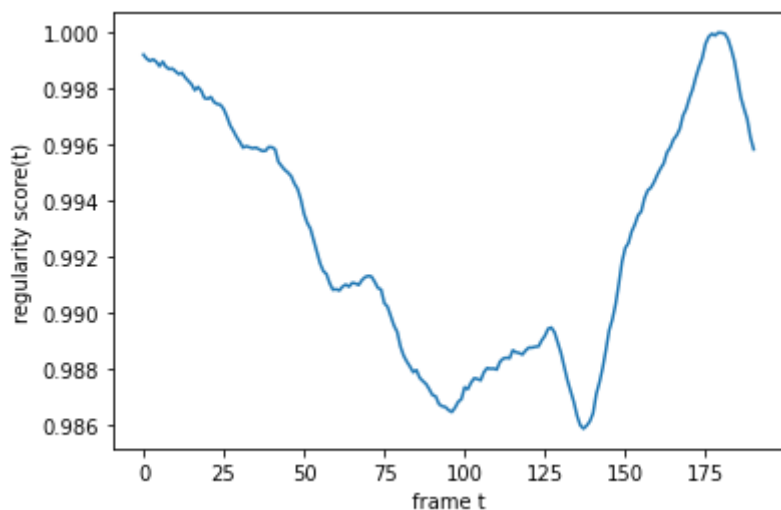
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test026

GT: 26

got model

(200, 227, 227, 1)

got data

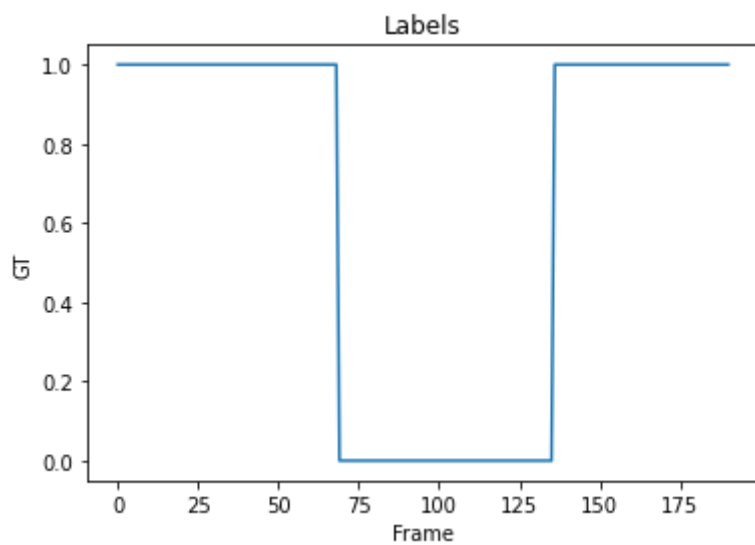
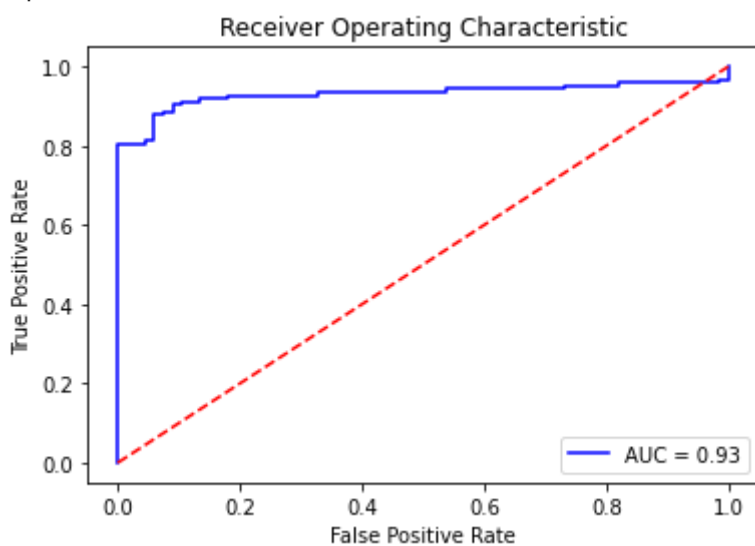


AUC: 0.9306692344727974

EER: 0.08955223880597014

EER THRESHOLD: 0.9907851614574545

Optimal threshold value is: 0.9909204029240108



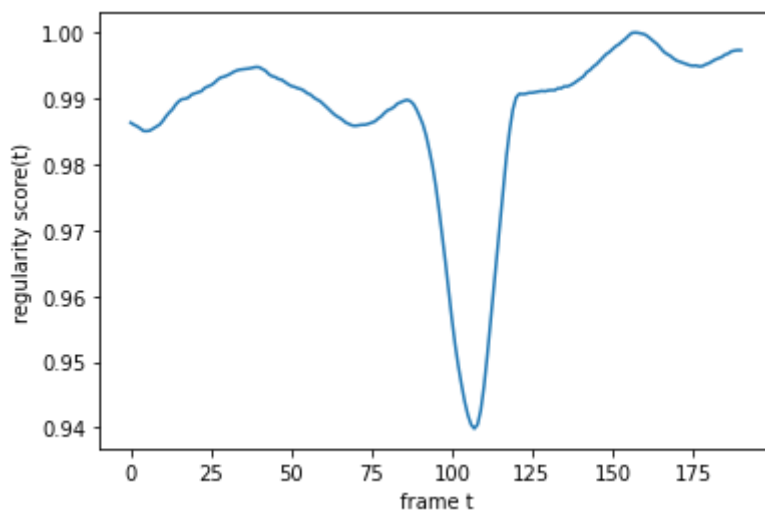
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test027

GT: 27

got model

(200, 227, 227, 1)

got data

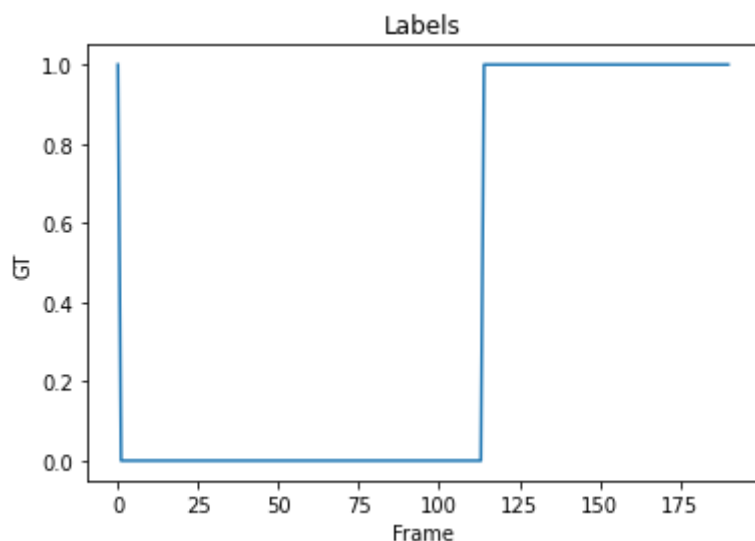
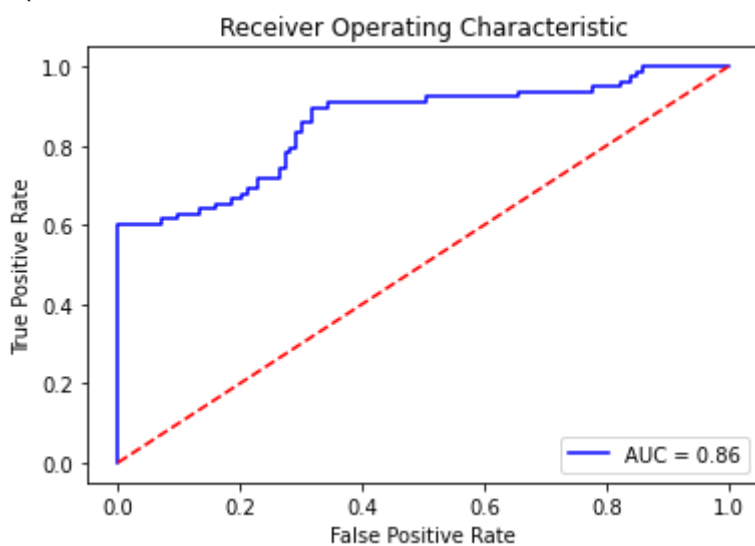


AUC: 0.8557975947356478

EER: 0.26548672566371684

EER THRESHOLD: 0.9915194228022246

Optimal threshold value is: 0.9947984979406236



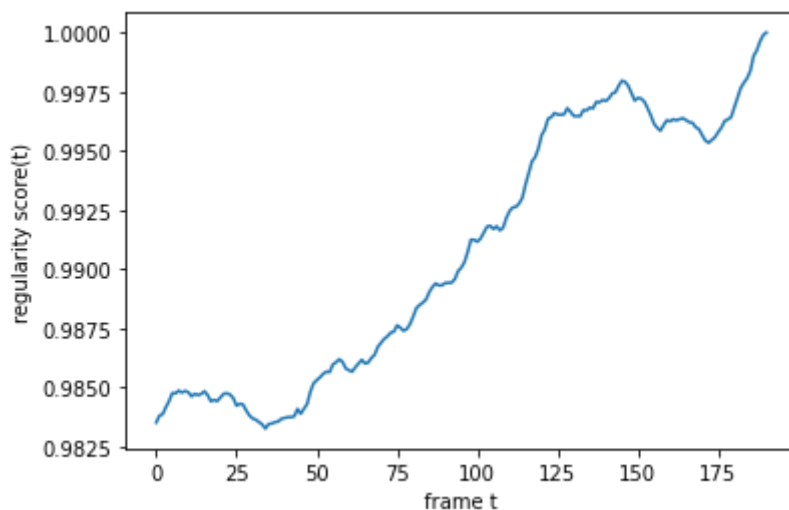
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test028

GT: 28

got model

(200, 227, 227, 1)

got data

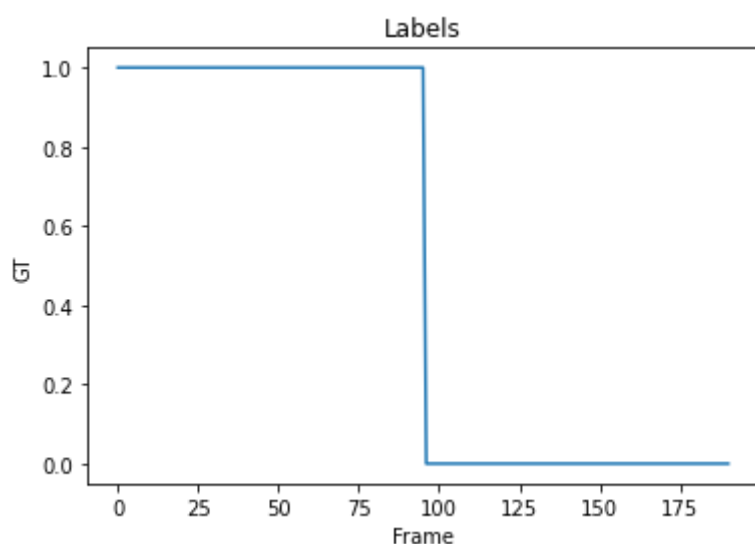
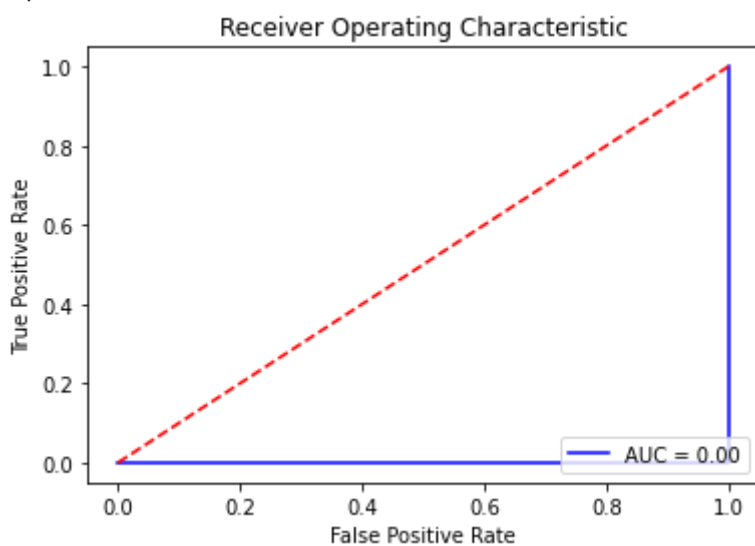


AUC: 0.0

EER: 1.0

EER THRESHOLD: 0.9902996203898919

Optimal threshold value is: 2.0



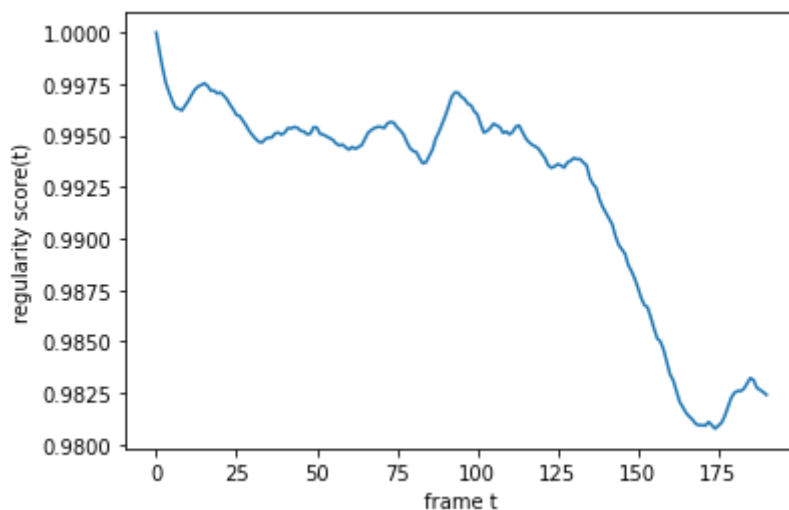
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test029

GT: 29

got model

(200, 227, 227, 1)

got data

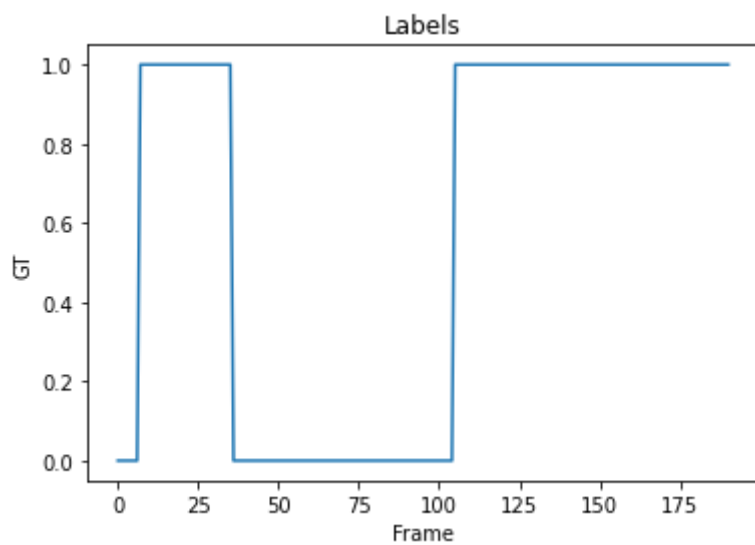
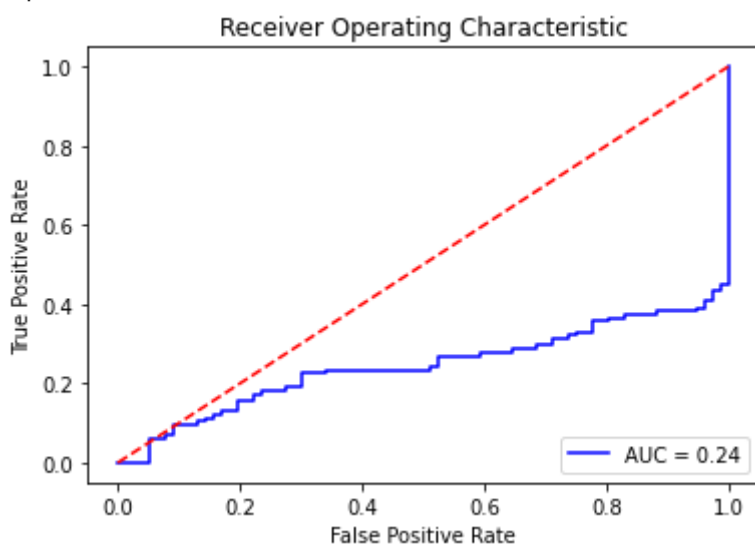


AUC: 0.24382151029748286

EER: 0.7105263157894737

EER THRESHOLD: 0.994904464217343

Optimal threshold value is: 0.9971800478413467



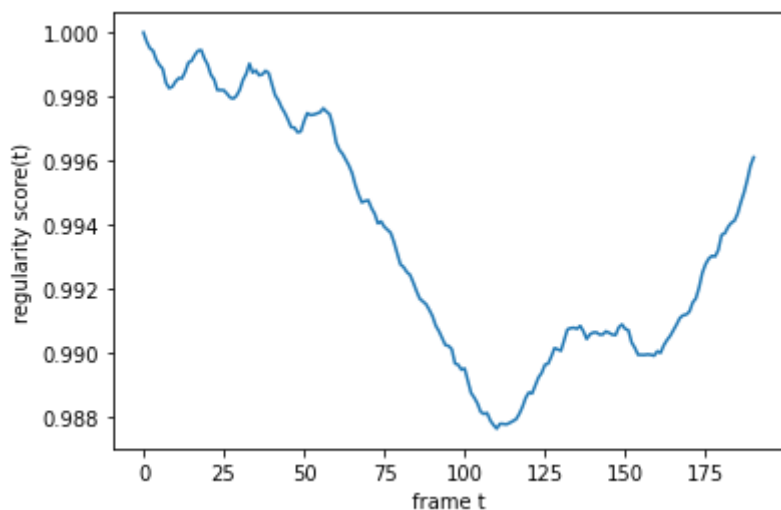
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test030

GT: 30

got model

(200, 227, 227, 1)

got data

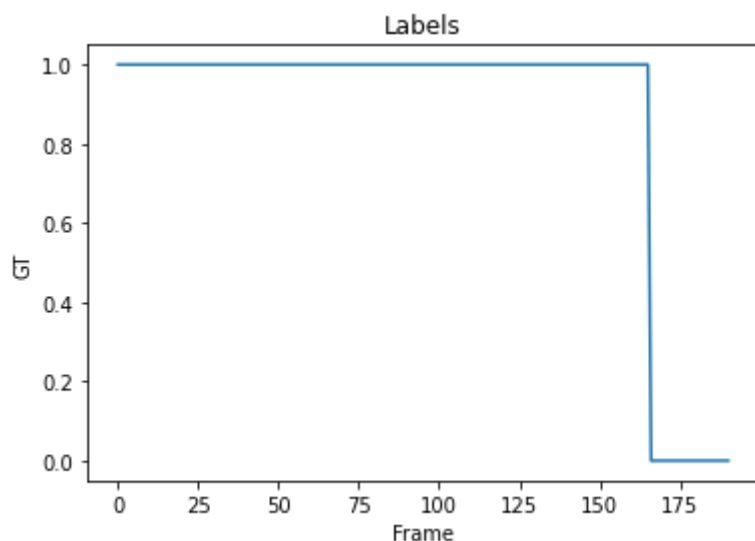
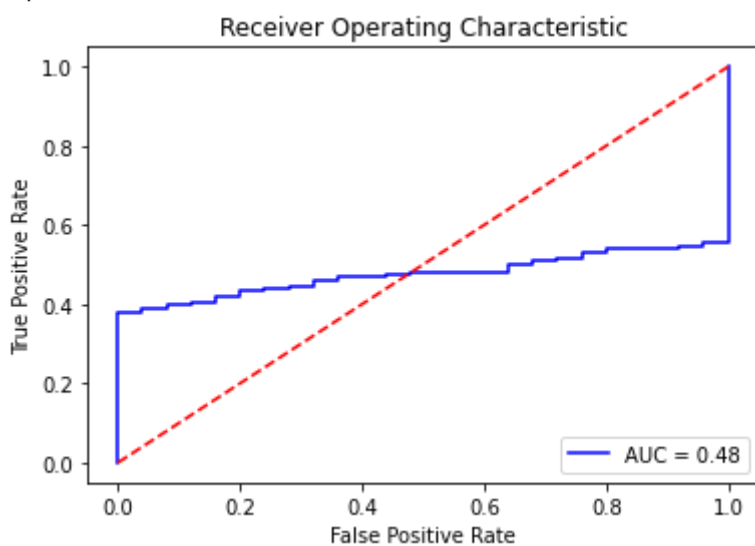


AUC: 0.4761445783132531

EER: 0.48

EER THRESHOLD: 0.9931200708512489

Optimal threshold value is: 0.9962185845343665



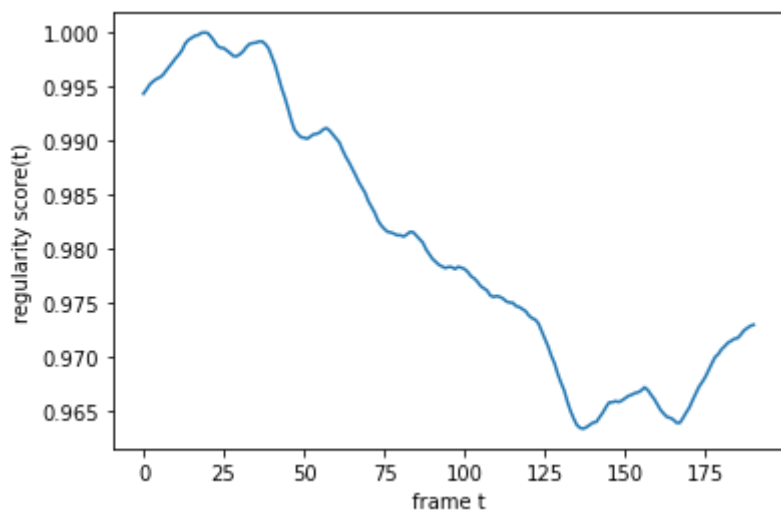
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test031

GT: 31

got model

(200, 227, 227, 1)

got data

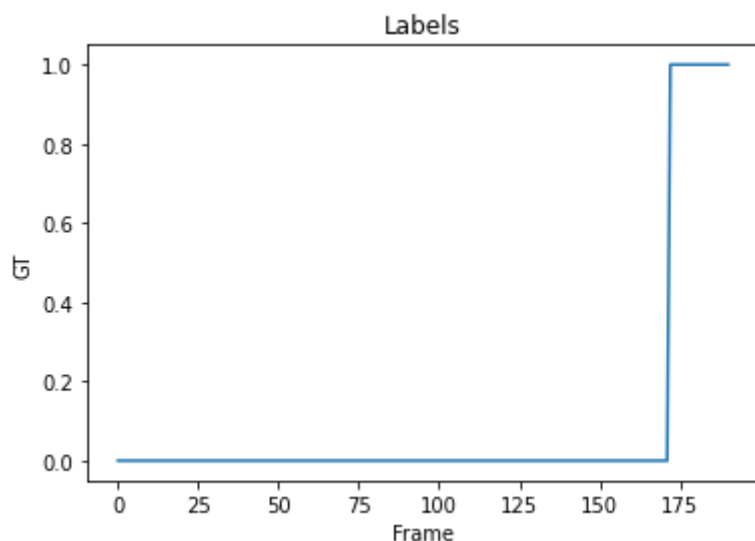
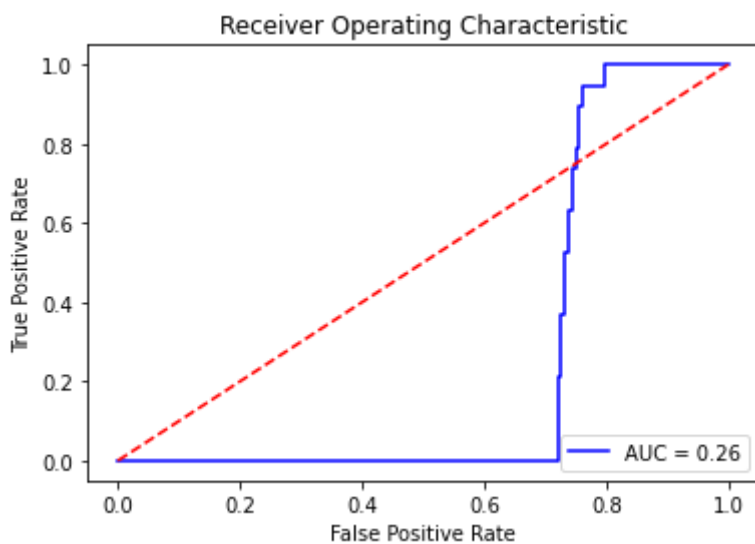


AUC: 0.26070991432068547

EER: 0.7267441860465116

EER THRESHOLD: 0.9724247640801621

Optimal threshold value is: 0.9666916064894348



PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test032

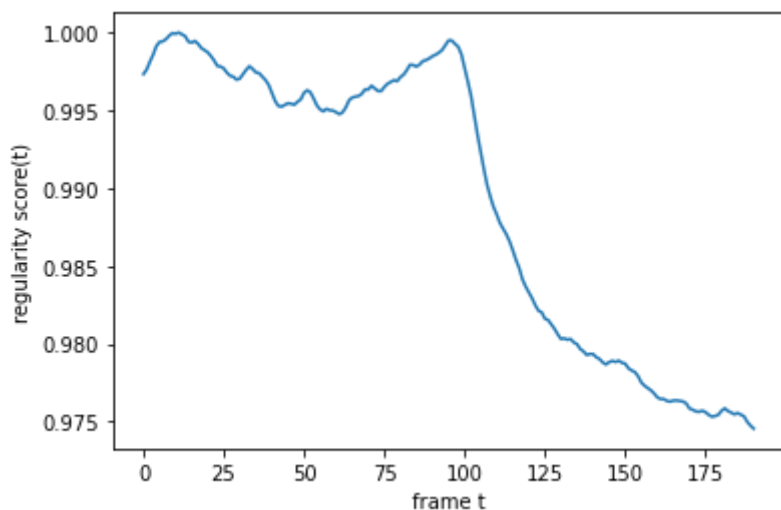
GT: 32

got model

(200, 227, 227, 1)

got data



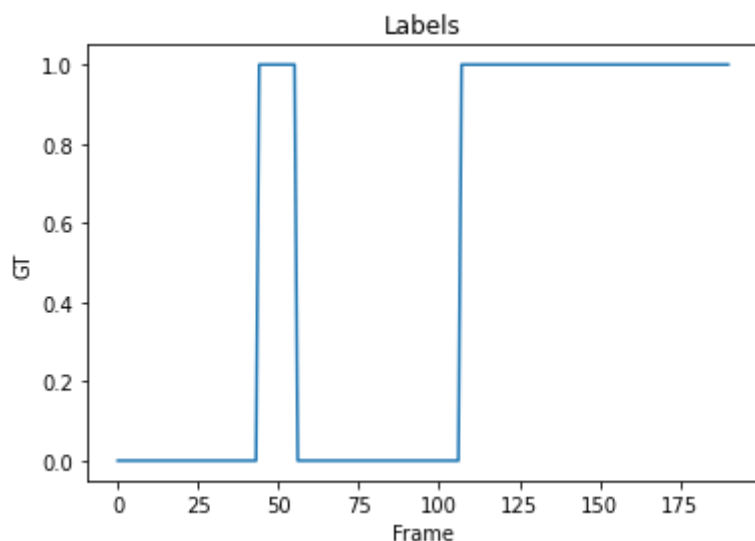
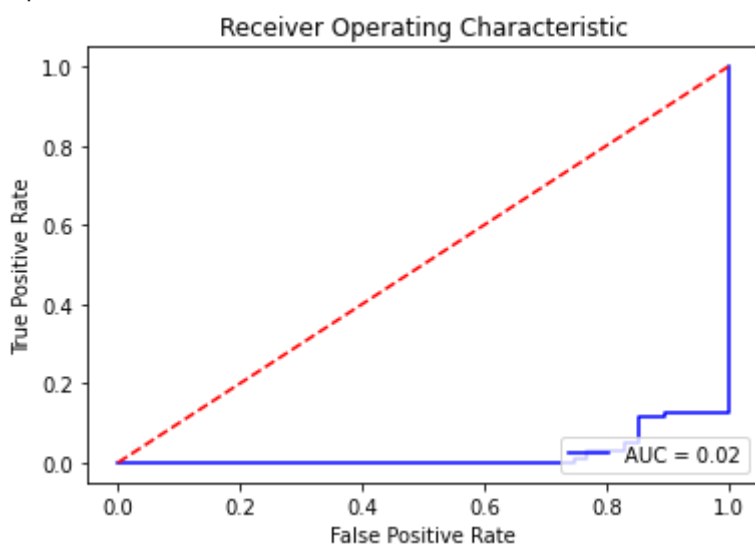


AUC: 0.021271929824561404

EER: 0.8947368421052632

EER THRESHOLD: 0.9950976292890535

Optimal threshold value is: 2.0



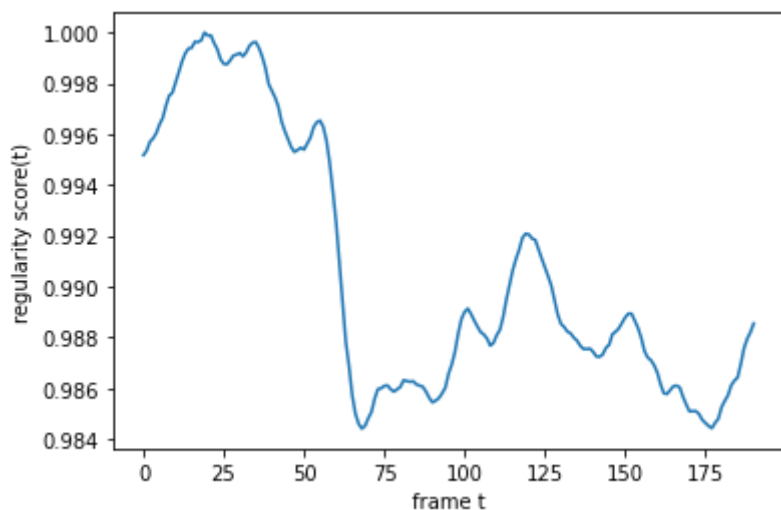
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test033

GT: 33

got model

(200, 227, 227, 1)

got data

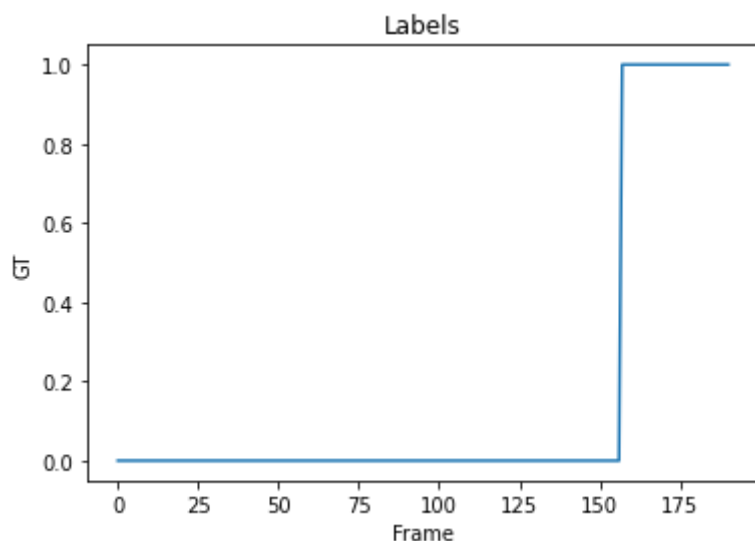
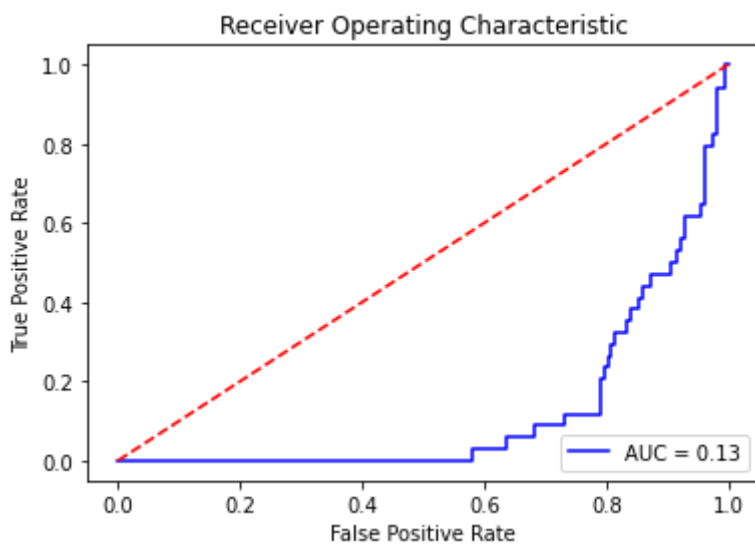


AUC: 0.12532783814162607

EER: 0.7961783439490446

EER THRESHOLD: 0.9869319638317873

Optimal threshold value is: 0.9844201956651223



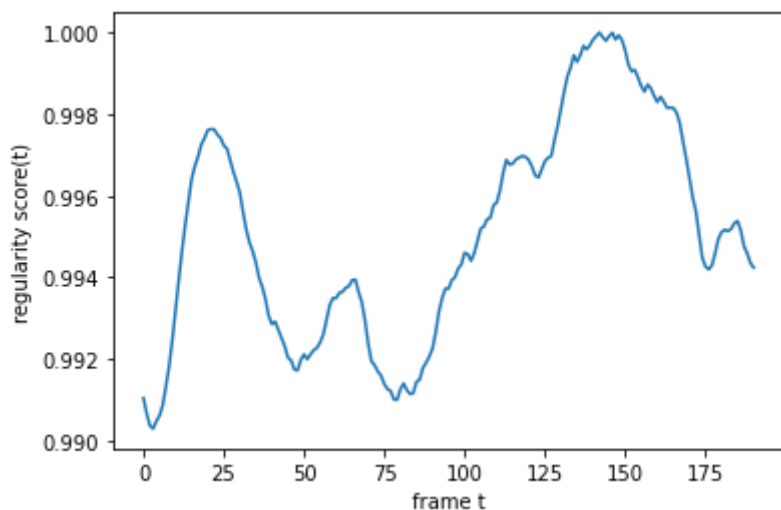
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test034

GT: 34

got model

(200, 227, 227, 1)

got data

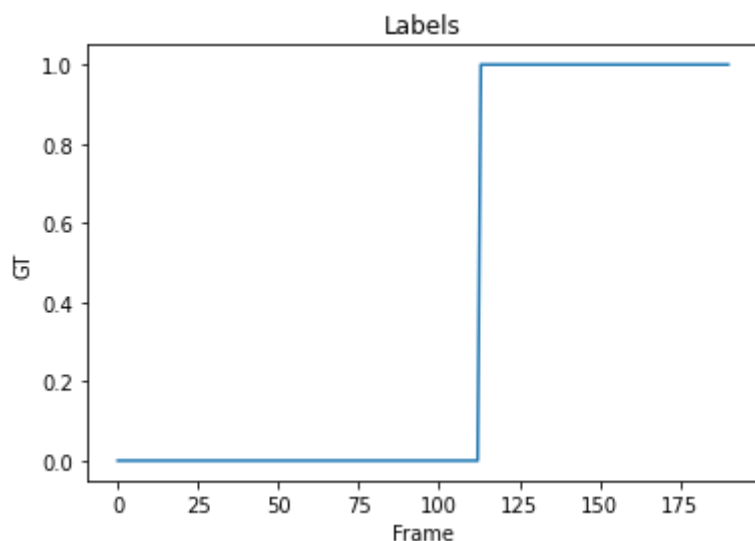
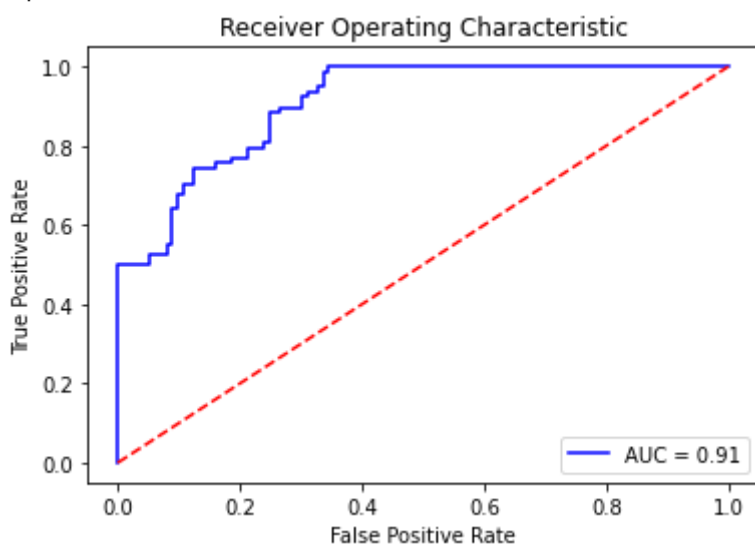


AUC: 0.9087814840027229

EER: 0.21238938053097345

EER THRESHOLD: 0.9953304895562725

Optimal threshold value is: 0.9941964849224201



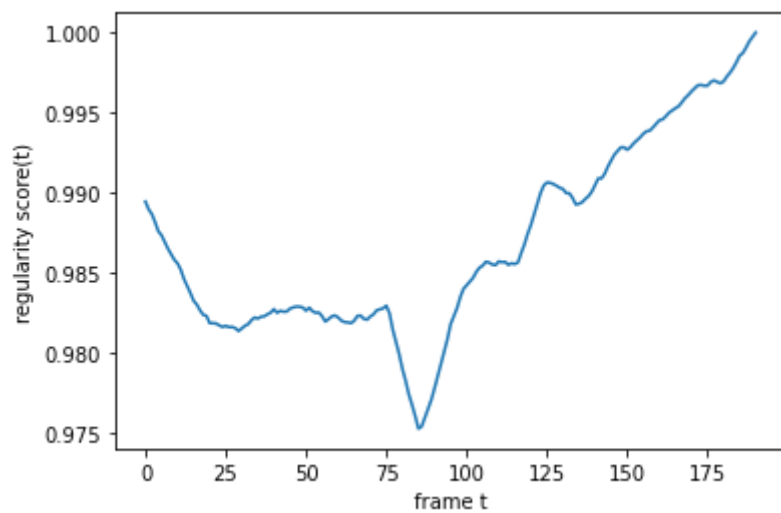
PATH: UCSD/UCSD\_Anomaly\_Dataset.v1p2/UCSDped1/Test/Test035

GT: 35

got model

(200, 227, 227, 1)

got data

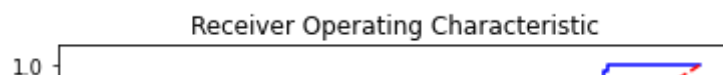


AUC: 0.20141262246525404

EER: 0.8070175438596491

EER THRESHOLD: 0.9837361944188204

Optimal threshold value is: 0.9813665937689471



In [13]:

```

"""
#manually counting tp, fp, tn, fn

#OUTCOME: very similar ROC and AUC, but this manual version would require changing the videos each time by hand

def multiTresh(pr):
    treshMin, treshMax, step=min(pr),max(pr),0.01
    treshold = treshMin
    dif=0
    rangeFrom, rangeTo = 59, 152+1 #range from the TestVideoFile[1]
    rate,pair=[],[]

    while(treshold<treshMax):
        treshold = treshold + step
        truePositive, falsePositive, falseNegative, trueNegative = 0,0,0,0

        for ii in range(len(pr)):
            if pr[ii]<treshold and ii in range(rangeFrom, rangeTo):
                truePositive +=1
            if pr[ii]<treshold and ii not in range(rangeFrom, rangeTo):
                falsePositive += 1
            if pr[ii]>treshold and ii in range(rangeFrom, rangeTo):
                falseNegative +=1
            if pr[ii]>treshold and ii not in range(rangeFrom, rangeTo):
                trueNegative += 1
        pair=[]
        tpr=truePositive/(truePositive + falseNegative)
        pair.append(tpr)
        fpr=falsePositive/(trueNegative+ falsePositive )
        pair.append(fpr)
        rate.append(pair)
    return rate

pairs=multiTresh(pr)
for ii in range(len(pairs)):
    print(pairs[ii])

roc_point = pairs
pivot = pd.DataFrame(roc_point, columns = ["x", "y"])
pivot

#ROC
plt.scatter(pivot.y, pivot.x)
plt.plot([0,1])
plt.xlabel('false positive rate')
plt.ylabel('true positive rate')

#AUC
from numpy import trapz
auc = np.trapz(pivot.x, pivot.y)
auc
"""

```

Out[13]:

```

'\n#manually counting tp, fp, tn, fn \n\n#OUTCOME: very similar ROC and AUC, but this manual version would require changing the videos each time by hand\n\nndef multiTresh(pr):\n    treshMin, treshMax, step=min(pr),max(pr),0.01\n    treshold = treshMin\n    dif=0\n    rangeFrom, rangeTo = 59, 152+1\n    #range from the TestVideoFile[1]\n    rate,pair=[],[]\n    \n    while (treshold<treshMax):\n        treshold = treshold + step\n        truePosit

```

```

ive, falsePositive, falseNegative, trueNegative = 0,0,0,0 \n      \n
for ii in range(len(pr)):\n      if pr[ii]<treshold and ii in range(r
angeFrom, rangeTo):\n      truePositive +=1\n      if pr[i
i]<treshold and ii not in range(rangeFrom, rangeTo):\n      false
Positive += 1 \n      if pr[ii]>treshold and ii in range(rangeFrom,
rangeTo):\n      falseNegative +=1\n      if pr[ii]>treshol
d and ii not in range(rangeFrom, rangeTo):\n      trueNegative +=
1 \n      pair=[]\n      tpr=truePositive/(truePositive + falseNegativ
e)\n      pair.append(tpr)\n      fpr=falsePositive/(trueNegative+ fals
ePositive )\n      pair.append(fpr)\n      rate.append(pair)\n      retur
n rate\n\n\npairs=multiTresh(pr)\nfor ii in range(len(pairs)):\n      print(p
airs[ii]) \n\nroc_point = pairs      \npivot = pd.DataFrame(roc_point, column
s = ["x", "y"])\npivot\n\n#ROC\nplt.scatter(pivot.y, pivot.x)\nplt.plot([0,
1])\nplt.xlabel('\false positive rate')\nplt.ylabel('\true positive rat
e')\n\n#AUC\nfrom numpy import trapz\nauc = np.trapz(pivot.x, pivot.y)\nau

```