```
import os
from google.colab import drive
drive. mount('/content/drive')
path = "/content/drive/My Drive/暑期科研/"
os. chdir (path)
os. listdir (path)
    Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force remount=True).
     ['chromosome 1 x train.npy',
      'chromosome 1 x test.npy',
      'chromosome 1 y test.npv'.
      'chromosome 1 y train.npy',
      'chromosome r y test.npy',
      'chromosome r y train.npy',
      'chromosome r x test.npy',
      'chromosome r x train.npy'
import glob
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from keras. preprocessing import image
from keras.models import Model
from keras.optimizers import Adam
from keras.callbacks import EarlyStopping
from keras.layers import Input, Dense, Activation, BatchNormalization, Flatten, Conv2D
from keras.layers import MaxPooling2D, Dropout, UpSampling2D
import os
x_train_savepath = './chromosome r x train.npy'
y_train_savepath = './chromosome r y train.npy'
```

```
x_test_savepath = './chromosome r x test.npy'
y test savepath = './chromosome r y test.npy'
print('----'Load Datasets----')
x train save = np. load(x train savepath)
y train = np. load(y train savepath)
x test save = np.load(x test savepath)
y test = np. load(y test savepath)
x train = np. reshape(x train save, (len(x train save), 150, 150, 1))
x \text{ test} = \text{np. reshape}(x \text{ test save}, (\text{len}(x \text{ test save}), 150, 150, 1))
x train = x train.astype('float32')
x test = x test.astype('float32')
# x train = x train.reshape((len(x train), np.prod(x train.shape[1:])))
\# x test = x test.reshape((len(x test), np.prod(x test.shape[1:])))
print(x train.shape)
print(x test. shape)
class Autoencoder():
       def init (self):
               self.img shape = (150, 150, 1)
               optimizer = Adam(1r=0.001)
               self.autoencoder model = self.build model()
               self.autoencoder model.compile(loss='binary_crossentropy', optimizer=optimizer)
                self. autoencoder model. summary()
        def build model(self):
               input layer = Input(shape=self.img shape)
                # encoder
               h = Conv2D(64, (3, 3), activation='relu', padding='same')(input layer)
               h = MaxPooling2D((2, 2), padding='same')(h)
               h = Conv2D(64, (3, 3), activation='relu', padding='same')(h)
               h = MaxPooling2D((3, 3), padding='same')(h)
```

```
# decoder
               h = Conv2D(64, (3, 3), activation='relu', padding='same')(h)
               h = UpSampling2D((3, 3))(h)
               h = Conv2D(64, (3, 3), activation='relu', padding='same')(h)
               h = UpSampling2D((2, 2))(h)
               output layer = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(h)
               return Model (input layer, output layer)
       def train model (self, x train, y train, x test, y test, epochs, batch size):
               early stopping = EarlyStopping(monitor='val loss',
                                                                           min delta=0,
                                                                           patience=5,
                                                                           verbose=1.
                                                                           mode='auto')
               history = self.autoencoder model.fit(x train, x train,
                                                                                      batch size=batch size,
                                                                                       epochs=epochs,
                                                                                       validation data=(x test, x test),
                                                                                       callbacks=[early stopping])
               plt. plot (history. history['loss'])
               plt.plot(history.history['val loss'])
               plt.title('Model loss')
               plt.ylabel('Loss')
               plt.xlabel('Epoch')
               plt.legend(['Train', 'Test'], loc='upper left')
               plt.show()
       def eval model(self, x test):
               preds = self.autoencoder model.predict(x test)
               return preds
ae = Autoencoder()
ae.train model(x train, x_train, x_test, x_test, epochs=20, batch_size=4)
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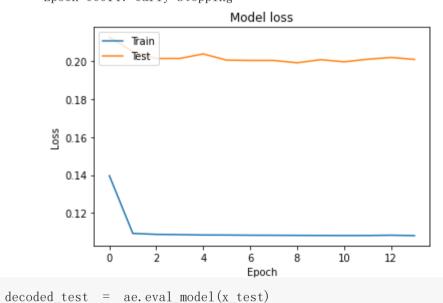
---Load Datasets----

(988, 150, 150, 1) (188, 150, 150, 1) Model: "model 2"

Layer (type)	Output	Shape	Param #
input_2 (InputLayer)	(None,	150, 150, 1)	0
conv2d_6 (Conv2D)	(None,	150, 150, 64)	640
max_pooling2d_3 (MaxPooling2	(None,	75, 75, 64)	0
conv2d_7 (Conv2D)	(None,	75, 75, 64)	36928
max_pooling2d_4 (MaxPooling2	(None,	25, 25, 64)	0
conv2d_8 (Conv2D)	(None,	25, 25, 64)	36928
up_sampling2d_3 (UpSampling2	(None,	75, 75, 64)	0
conv2d_9 (Conv2D)	(None,	75, 75, 64)	36928
up_sampling2d_4 (UpSampling2	(None,	150, 150, 64)	0
conv2d_10 (Conv2D)	(None,	150, 150, 1)	577

Total params: 112,001 Trainable params: 112,001 Non-trainable params: 0

```
Epoch 6/20
                               =] - 6s 6ms/step - loss: 0.1084 - val loss: 0.2005
Epoch 7/20
Epoch 8/20
                               ==] - 6s 6ms/step - loss: 0.1082 - val loss: 0.2004
988/988 [===
Epoch 9/20
                               == ] - 6s 6ms/step - loss: 0.1082 - val loss: 0.1992
988/988 [====
Epoch 10/20
988/988 [====
                      =======] - 6s 6ms/step - loss: 0.1082 - val loss: 0.2008
Epoch 11/20
                               == ] - 6s 6ms/step - loss: 0.1081 - val loss: 0.1997
988/988 [====
Epoch 12/20
                      ======== ] - 6s 6ms/step - loss: 0.1081 - val loss: 0.2010
988/988 [===
Epoch 13/20
                               ==] - 6s 6ms/step - loss: 0.1083 - val loss: 0.2020
988/988 [====
Epoch 14/20
988/988 [============] - 6s 6ms/step - loss: 0.1081 - val loss: 0.2009
Epoch 00014: early stopping
```



import matplotlib.pyplot as plt
%matplotlib inline
shape = (150, 150)
fig axes = plt subplots(2.10)

```
115, and probable (4, 10,
                                               figsize=(10, 2),
                                               subplot kw={
                                                       'xticks': [],
                                                       'yticks': []
                                               gridspec kw=dict(hspace=0.1, wspace=0.1))
for i in range (10):
       axes[0][i]. imshow(np. reshape(x test[i], shape), cmap='gray')
       axes[1][i].imshow(np.reshape(decoded test[i], shape), cmap='gray')
plt.show()
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### get the error term of all testing dataset images
from sklearn.preprocessing import StandardScaler, MinMaxScaler
scaler = MinMaxScaler()
#scale it
scaled input test = scaler.fit transform(x test.reshape(-1,22500))
#scale it
scaled output test = scaler.fit transform(decoded test.reshape(-1, 22500))
```

```
#### get the error term of all training set images

# Firstly, we get the decoder image of training set.
decoded_train = ae.eval_model(x_train)

from sklearn.preprocessing import StandardScaler, MinMaxScaler
scaler = MinMaxScaler()
#scale it
scaled_input_train = scaler.fit_transform(x_train.reshape(-1,22500))
```

```
#scale it
scaled_output_train = scaler.fit_transform(decoded_train.reshape(-1,22500))

import pandas as pd
sequences = range(1,1177)

from keras import losses
x = losses.binary_crossentropy(scaled_input_train, scaled_output_train)
y = losses.binary_crossentropy(scaled_input_test, scaled_output_test)

seqs_ds = pd. DataFrame(sequences)
mse = np. append(x, y)
seqs_ds['MSE'] = mse
seqs_ds
```

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```
mse threshold = np.quantile(seqs ds['MSE'], 0.84)
print(f'MSE 0.9 threshhold:{mse threshold}')
 MSE 0.9 threshhold:1.5023871660232544
       2
               3 1.418232
segs ds['MSE Outlier'] = 0
seqs ds.loc[seqs ds['MSE'] > mse threshold, 'MSE Outlier'] = 1
print(f"Num of MSE outlier:{seqs ds['MSE Outlier'].sum()}")
seqs ds[seqs ds['MSE Outlier']==1]
     Num of MSE outlier:188
                       MSE MSE Outlier
               0
      818
             819 1.505959
             989 2.506710
      988
      989
             990 1.950874
      990
             991 1.784902
      991
             992 1.775405
```

1171 1172 1.845395 1172 1173 2.576621

1173 1174 2.489601

1174 1175 2.455830

1175 1176 2.434648

188 rows × 3 columns