## Generic-Semantic-Melanoma-Segment-Unet++ (G)

March 23, 2023

### 1 Segment using Unet++

```
[86]: #Libraries---
      import os
      import random
      import pandas as pd
      import numpy as np
      import matplotlib.pyplot as plt
      import warnings
      import gc
      from pathlib import Path
      from tqdm.notebook import trange, tqdm
      from itertools import chain
      from skimage.io import imread, imshow, concatenate_images
      from skimage.transform import resize
      from skimage.morphology import label
      from sklearn.model_selection import train_test_split
      import glob
      import cv2
      from PIL import Image
      import glob2
      from tensorflow.keras.models import load_model
      import tensorflow
      import tensorflow as tf
      from tensorflow.keras.preprocessing.image import ImageDataGenerator, u
       →array_to_img, img_to_array, load_img
      from tensorflow.keras.layers import Conv2D, Input, MaxPooling2D, Dropout,
       ⇔concatenate, UpSampling2D
      from tensorflow.keras.models import load_model, Model
      from tensorflow.keras.optimizers import Adam
      from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint,
       →ReduceLROnPlateau, TensorBoard
      from tensorflow.keras import backend as K
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import (BatchNormalization, Conv2DTranspose,
                                           SeparableConv2D, MaxPooling2D, Activation,
       →Flatten, Dropout, Dense)
```

```
from tensorflow.keras.preprocessing.image import load_img, array_to_img,_
 →img_to_array
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Conv2D, LeakyReLU, BatchNormalization,
 →MaxPool2D,Conv2DTranspose, concatenate,Input
from tensorflow.keras.callbacks import CSVLogger
from tensorflow.keras.utils import plot_model
import pickle
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import sklearn
from sklearn.cluster import KMeans
from tensorflow.keras.layers import *
from tensorflow.keras import models
from tensorflow.keras.callbacks import *
from tensorflow.keras.applications import ResNet50
from sklearn.utils import shuffle
import matplotlib.pyplot as plt
from tensorflow.keras.metrics import MeanIoU
K.clear_session()
warnings.filterwarnings('ignore')
plt.style.use("ggplot")
get_ipython().run_line_magic('matplotlib', 'inline')
```

## 2 Reding and Preprocessing images

```
[87]: #Load image data--
      H,W,CH=[128,128,3]
      def cv_load_img(path):
         img= cv2.imread(path)
          img= cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
          img=cv2.resize(img,(W,H))
         return img
[88]: #Load data-----
      BASE_DIR="Melanoma/train/"
      img_path= os.listdir(BASE_DIR+'images')
      mask_path= os.listdir(BASE_DIR+'masks')
[89]: #plot sample images-----
      fig, ax= plt.subplots(1,5, figsize=(20, 10))
      for i in range(5):
         path= BASE_DIR + 'images/'
         ax[i].imshow(load_img(path + img_path[i]))
         ax[i].set_xticks([]); ax[i].set_yticks([])
```

```
fig.tight_layout()
plt.show()
```











```
[90]: #plot sample masks------
fig, ax= plt.subplots(1,5, figsize=(20, 10))
for i in range(5):
    path= BASE_DIR + 'masks/'
    ax[i].imshow(cv_load_img(path + mask_path[i])[:, :, 0], 'gray')
    ax[i].set_xticks([]); ax[i].set_yticks([])

fig.tight_layout()
plt.show()
```







## 3 Augmented Images and Masks

```
[92]: #data preparation
     X_train, X_test, y_train, y_test = train_test_split(img_path, mask_path,_
       ⇔test_size=0.2, random_state=22)
     len(X_train), len(X_test)
[92]: (164, 42)
[93]: #batch generation-----
     def load_data(path_list, gray=False):
         data=[]
         for path in tqdm(path_list):
             img= cv_load_img(path)
              if gray:
                 img= img[:, :, 0:1]
              img= cv2.resize(img, (W, H))
              data.append(img)
         return np.array(data)
[94]: #train data generation-----
     X_train= load_data([BASE_DIR + 'images/' + x for x in X_train])/255.0
     X_test= load_data([BASE_DIR + 'images/' + x for x in X_test])/255.0
       0%1
                    | 0/164 [00:00<?, ?it/s]
       0%1
                    | 0/42 [00:00<?, ?it/s]
[95]: ##test data generation-----
     Y_train= load_data([BASE_DIR + 'masks/' + x for x in y_train], gray=True)/255.0
     Y_test= load_data([BASE_DIR + 'masks/' + x for x in y_test], gray=True)/255.0
     Y_train= Y_train.reshape(-1, W, H, 1)
     Y_test= Y_test.reshape(-1, W, H, 1)
     Y_train.shape, Y_test.shape
       0%1
                    | 0/164 [00:00<?, ?it/s]
       0%1
                    | 0/42 [00:00<?, ?it/s]
[95]: ((164, 128, 128, 1), (42, 128, 128, 1))
     # Unet Model
```

```
[96]: def Conv2dBlock(inputTensor, numFilters, kernelSize = 3, doBatchNorm = True):
         #first Conv
         x = tf.keras.layers.Conv2D(filters = numFilters, kernel_size = (kernelSize, __
       ⇔kernelSize),
                                   kernel_initializer = 'he_normal', padding =__
       if doBatchNorm:
             x = tf.keras.layers.BatchNormalization()(x)
         x =tf.keras.layers.Activation('relu')(x)
         #Second Conv
         x = tf.keras.layers.Conv2D(filters = numFilters, kernel_size = (kernelSize, _
       ⇔kernelSize),
                                   kernel_initializer = 'he_normal', padding =__
       if doBatchNorm:
             x = tf.keras.layers.BatchNormalization()(x)
         x = tf.keras.layers.Activation('relu')(x)
         return x
      # Now defining Unet
      def GiveMeUnet(inputImage, numFilters = 16, droupouts = 0.1, doBatchNorm = 1
       →True):
          # defining encoder Path
         c1 = Conv2dBlock(inputImage, numFilters * 1, kernelSize = 3, doBatchNorm = ___
       →doBatchNorm)
         p1 = tf.keras.layers.MaxPooling2D((2,2))(c1)
         p1 = tf.keras.layers.Dropout(droupouts)(p1)
         c2 = Conv2dBlock(p1, numFilters * 2, kernelSize = 3, doBatchNorm = __
       →doBatchNorm)
         p2 = tf.keras.layers.MaxPooling2D((2,2))(c2)
         p2 = tf.keras.layers.Dropout(droupouts)(p2)
         c3 = Conv2dBlock(p2, numFilters * 4, kernelSize = 3, doBatchNorm =__
       →doBatchNorm)
         p3 = tf.keras.layers.MaxPooling2D((2,2))(c3)
         p3 = tf.keras.layers.Dropout(droupouts)(p3)
         c4 = Conv2dBlock(p3, numFilters * 8, kernelSize = 3, doBatchNorm = _
       →doBatchNorm)
```

```
p4 = tf.keras.layers.Dropout(droupouts)(p4)
         c5 = Conv2dBlock(p4, numFilters * 16, kernelSize = 3, doBatchNorm = 1
       →doBatchNorm)
         # defining decoder path
         u6 = tf.keras.layers.Conv2DTranspose(numFilters*8, (3, 3), strides = (2, 1)
      42), padding = 'same')(c5)
         u6 = tf.keras.layers.concatenate([u6, c4])
         u6 = tf.keras.layers.Dropout(droupouts)(u6)
         c6 = Conv2dBlock(u6, numFilters * 8, kernelSize = 3, doBatchNorm =_
       →doBatchNorm)
         \hookrightarrow2), padding = 'same')(c6)
         u7 = tf.keras.layers.concatenate([u7, c3])
         u7 = tf.keras.layers.Dropout(droupouts)(u7)
         c7 = Conv2dBlock(u7, numFilters * 4, kernelSize = 3, doBatchNorm =_
       →doBatchNorm)
         u8 = tf.keras.layers.Conv2DTranspose(numFilters*2, (3, 3), strides = (2, u)
      \hookrightarrow2), padding = 'same')(c7)
         u8 = tf.keras.layers.concatenate([u8, c2])
         u8 = tf.keras.layers.Dropout(droupouts)(u8)
         c8 = Conv2dBlock(u8, numFilters * 2, kernelSize = 3, doBatchNorm = __
       →doBatchNorm)
         \hookrightarrow2), padding = 'same')(c8)
         u9 = tf.keras.layers.concatenate([u9, c1])
         u9 = tf.keras.layers.Dropout(droupouts)(u9)
         c9 = Conv2dBlock(u9, numFilters * 1, kernelSize = 3, doBatchNorm = _ _
       →doBatchNorm)
         output = tf.keras.layers.Conv2D(1, (1, 1), activation = 'sigmoid')(c9)
         model = tf.keras.Model(inputs = [inputImage], outputs = [output])
         return model
[97]: def dice_loss(y_true, y_pred):
         numerator = tf.reduce_sum(y_true * y_pred)
         denominator = tf.reduce_sum(y_true * y_true) + tf.reduce_sum(y_pred *_
       →y_pred) - tf.reduce_sum(y_true * y_pred)
```

p4 = tf.keras.layers.MaxPooling2D((2,2))(c4)

```
return 1 - numerator / denominator
[112]: smooth =100
      def iou(y_true, y_pred):
          intersection = K.sum(y_true * y_pred)
          sum_ = K.sum(y_true + y_pred)
          jac = (intersection + smooth) / (sum_ - intersection + smooth)
          return jac
[98]: def jacard_coef(y_true, y_pred):
          y_true_f = K.flatten(y_true)
          y_pred_f = K.flatten(y_pred)
          intersection = K.sum(y_true_f * y_pred_f)
          return (intersection + 1.0) / (K.sum(y_true_f) + K.sum(y_pred_f) - U
       ⇒intersection + 1.0)
[99]: metrics=['accuracy', jacard_coef, iou]
      inputs = tf.keras.layers.Input((H, W, CH))
      model = GiveMeUnet(inputs, droupouts= 0.07)
      model.compile(optimizer = 'Adam', loss = dice_loss, metrics =metrics)#loss =__
       ⇒binary_crossentropy "binary_accuracy",
     4 Model Summary
[100]: #Summary of model-----
      model.summary()
      #Plot of model----
      dot_img_file = 'model.png'
      plot_model(model, to_file=dot_img_file, show_shapes=True)
     Model: "model"
      Layer (type)
                                   Output Shape
                                                      Param #
                                                                 Connected to
     ______
                                  [(None, 128, 128, 3 0
      input_1 (InputLayer)
                                                                 )]
      conv2d (Conv2D)
                                   (None, 128, 128, 16 448
      ['input_1[0][0]']
                                   )
```

```
batch_normalization (BatchNorm (None, 128, 128, 16 64
['conv2d[0][0]']
                                )
alization)
activation (Activation)
                                (None, 128, 128, 16 0
['batch_normalization[0][0]']
                                )
conv2d_1 (Conv2D)
                                (None, 128, 128, 16 2320
['activation[0][0]']
                                )
batch_normalization_1 (BatchNo (None, 128, 128, 16 64
['conv2d_1[0][0]']
rmalization)
activation_1 (Activation)
                                (None, 128, 128, 16 0
['batch_normalization_1[0][0]']
                                )
max_pooling2d (MaxPooling2D)
                                (None, 64, 64, 16)
['activation_1[0][0]']
dropout (Dropout)
                                 (None, 64, 64, 16)
                                                      0
['max_pooling2d[0][0]']
conv2d_2 (Conv2D)
                                (None, 64, 64, 32)
                                                      4640
['dropout[0][0]']
batch_normalization_2 (BatchNo
                                 (None, 64, 64, 32)
                                                      128
['conv2d_2[0][0]']
rmalization)
activation_2 (Activation)
                                (None, 64, 64, 32)
['batch_normalization_2[0][0]']
conv2d_3 (Conv2D)
                                 (None, 64, 64, 32)
                                                      9248
['activation_2[0][0]']
batch_normalization_3 (BatchNo (None, 64, 64, 32)
                                                      128
['conv2d_3[0][0]']
rmalization)
activation_3 (Activation)
                                 (None, 64, 64, 32)
['batch_normalization_3[0][0]']
max_pooling2d_1 (MaxPooling2D)
                                 (None, 32, 32, 32)
['activation_3[0][0]']
```

```
dropout_1 (Dropout)
                                 (None, 32, 32, 32)
                                                      0
['max_pooling2d_1[0][0]']
conv2d 4 (Conv2D)
                                 (None, 32, 32, 64)
                                                      18496
['dropout_1[0][0]']
batch_normalization_4 (BatchNo
                                 (None, 32, 32, 64)
                                                      256
['conv2d_4[0][0]']
rmalization)
activation_4 (Activation)
                                 (None, 32, 32, 64)
                                                      0
['batch_normalization_4[0][0]']
conv2d_5 (Conv2D)
                                 (None, 32, 32, 64)
                                                      36928
['activation_4[0][0]']
batch_normalization_5 (BatchNo (None, 32, 32, 64)
                                                      256
['conv2d_5[0][0]']
rmalization)
activation_5 (Activation)
                                 (None, 32, 32, 64)
['batch_normalization_5[0][0]']
max_pooling2d_2 (MaxPooling2D)
                                 (None, 16, 16, 64)
['activation_5[0][0]']
dropout_2 (Dropout)
                                 (None, 16, 16, 64)
['max_pooling2d_2[0][0]']
                                 (None, 16, 16, 128)
conv2d_6 (Conv2D)
                                                      73856
['dropout_2[0][0]']
batch_normalization_6 (BatchNo (None, 16, 16, 128)
['conv2d 6[0][0]']
rmalization)
activation_6 (Activation)
                                 (None, 16, 16, 128)
['batch_normalization_6[0][0]']
conv2d_7 (Conv2D)
                                 (None, 16, 16, 128)
                                                      147584
['activation_6[0][0]']
batch_normalization_7 (BatchNo
                                 (None, 16, 16, 128)
['conv2d_7[0][0]']
rmalization)
activation_7 (Activation)
                                 (None, 16, 16, 128) 0
```

```
['batch_normalization_7[0][0]']
max_pooling2d_3 (MaxPooling2D)
                                 (None, 8, 8, 128)
                                                      0
['activation_7[0][0]']
dropout_3 (Dropout)
                                 (None, 8, 8, 128)
                                                      0
['max_pooling2d_3[0][0]']
conv2d_8 (Conv2D)
                                 (None, 8, 8, 256)
                                                      295168
['dropout_3[0][0]']
batch_normalization_8 (BatchNo (None, 8, 8, 256)
                                                      1024
['conv2d_8[0][0]']
rmalization)
activation_8 (Activation)
                                 (None, 8, 8, 256)
                                                      0
['batch_normalization_8[0][0]']
                                 (None, 8, 8, 256)
conv2d_9 (Conv2D)
                                                      590080
['activation_8[0][0]']
batch_normalization_9 (BatchNo
                                 (None, 8, 8, 256)
                                                      1024
['conv2d_9[0][0]']
rmalization)
activation_9 (Activation)
                                 (None, 8, 8, 256)
['batch_normalization_9[0][0]']
conv2d_transpose (Conv2DTransp
                                 (None, 16, 16, 128)
                                                       295040
['activation_9[0][0]']
ose)
concatenate (Concatenate)
                                 (None, 16, 16, 256) 0
['conv2d_transpose[0][0]',
'activation_7[0][0]']
dropout 4 (Dropout)
                                 (None, 16, 16, 256)
['concatenate[0][0]']
conv2d_10 (Conv2D)
                                 (None, 16, 16, 128)
                                                      295040
['dropout_4[0][0]']
batch_normalization_10 (BatchN (None, 16, 16, 128)
['conv2d_10[0][0]']
ormalization)
activation_10 (Activation)
                                 (None, 16, 16, 128) 0
['batch_normalization_10[0][0]']
```

```
conv2d_11 (Conv2D)
                                (None, 16, 16, 128)
                                                     147584
['activation_10[0][0]']
batch_normalization_11 (BatchN (None, 16, 16, 128)
['conv2d_11[0][0]']
ormalization)
activation_11 (Activation)
                                (None, 16, 16, 128) 0
['batch_normalization_11[0][0]']
conv2d_transpose_1 (Conv2DTran
                                (None, 32, 32, 64)
                                                     73792
['activation_11[0][0]']
spose)
concatenate_1 (Concatenate)
                                (None, 32, 32, 128) 0
['conv2d_transpose_1[0][0]',
'activation_5[0][0]']
dropout 5 (Dropout)
                                (None, 32, 32, 128)
['concatenate_1[0][0]']
conv2d_12 (Conv2D)
                                (None, 32, 32, 64)
                                                      73792
['dropout_5[0][0]']
batch_normalization_12 (BatchN (None, 32, 32, 64)
                                                      256
['conv2d_12[0][0]']
ormalization)
activation_12 (Activation)
                                (None, 32, 32, 64)
['batch_normalization_12[0][0]']
conv2d_13 (Conv2D)
                                (None, 32, 32, 64)
                                                      36928
['activation_12[0][0]']
batch_normalization_13 (BatchN (None, 32, 32, 64)
                                                      256
['conv2d 13[0][0]']
ormalization)
                                (None, 32, 32, 64)
activation_13 (Activation)
['batch_normalization_13[0][0]']
conv2d_transpose_2 (Conv2DTran (None, 64, 64, 32)
                                                      18464
['activation_13[0][0]']
spose)
concatenate_2 (Concatenate)
                                (None, 64, 64, 64)
['conv2d_transpose_2[0][0]',
```

```
'activation_3[0][0]']
dropout_6 (Dropout)
                                (None, 64, 64, 64)
['concatenate_2[0][0]']
conv2d_14 (Conv2D)
                                 (None, 64, 64, 32)
                                                      18464
['dropout_6[0][0]']
batch_normalization_14 (BatchN (None, 64, 64, 32)
                                                      128
['conv2d_14[0][0]']
ormalization)
activation_14 (Activation)
                                 (None, 64, 64, 32)
                                                      0
['batch_normalization_14[0][0]']
conv2d_15 (Conv2D)
                                 (None, 64, 64, 32)
                                                      9248
['activation_14[0][0]']
batch_normalization_15 (BatchN (None, 64, 64, 32)
                                                      128
['conv2d 15[0][0]']
ormalization)
activation_15 (Activation)
                                 (None, 64, 64, 32)
['batch_normalization_15[0][0]']
conv2d_transpose_3 (Conv2DTran (None, 128, 128, 16 4624
['activation_15[0][0]']
                                )
spose)
concatenate_3 (Concatenate)
                                (None, 128, 128, 32 0
['conv2d_transpose_3[0][0]',
                                )
'activation_1[0][0]']
dropout 7 (Dropout)
                                (None, 128, 128, 32 0
['concatenate_3[0][0]']
                                )
conv2d_16 (Conv2D)
                                (None, 128, 128, 16 4624
['dropout_7[0][0]']
                                )
batch_normalization_16 (BatchN (None, 128, 128, 16 64
['conv2d_16[0][0]']
                                )
ormalization)
activation_16 (Activation)
                                 (None, 128, 128, 16 0
['batch_normalization_16[0][0]']
```

```
)
     conv2d_17 (Conv2D)
                            (None, 128, 128, 16 2320
    ['activation_16[0][0]']
                            )
     batch_normalization_17 (BatchN (None, 128, 128, 16 64
    ['conv2d_17[0][0]']
     ormalization)
                            )
     activation_17 (Activation)
                            (None, 128, 128, 16 0
    ['batch_normalization_17[0][0]']
     conv2d_18 (Conv2D)
                            (None, 128, 128, 1) 17
    ['activation_17[0][0]']
    ______
    ______
    Total params: 2,164,593
    Trainable params: 2,161,649
    Non-trainable params: 2,944
    ______
[100]:
```

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```
Impac_1 Impac 8/2000, 129, 129, 129
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                                                                         Seed, pomelication Input (Nov., 128, 128, 16)
Date Novembroton Inspire (Nov., 128, 128, 16)
                                                                         solvation layer (Ponc, 128, 138, 16)
Activation segue: (Ponc, 128, 138, 16)
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Advation coper (New, 12, 12, 16)
                                              MacLanding M Sept. (New, 128, 128, 16)
MacPathing 21: Indiges. (News, 64, 64, 16)
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Drogeni oniquei (Neer, 64, 64, 16)
                                                hed_nomelineos_2 inpe: (Nos. 64.64.35)
BedNomelineos oupe: (Nos. 64.64.35)
                                            | mxNvsden 2 | input | (Fonc, 64, 64, 32) | AxStration | output | (Fonc, 64, 64, 32) | output | (Fonc, 64, 64, 32) | output | (Fonc, 64, 64, 12) | (Con/23) | output | (None, 64, 64, 12) |
                                       hish_normalisation_21 input: [Now, 64, 64, 32]
BathNormalisation output: [Now, 64, 64, 32]
                                            militation_E legen (Nove, 66, 66, 52)
Adminim colput (Nove, 66, 66, 52)
                                     max_posting$4_3 input: [20mm, 64, 64, 52]
MaxFeeling$3 majori [20mm, 53, 53, 52]
                                     Bropous , L. Begunt | Chican, 32, 52, 52)
| Despois | compant | Chican, 32, 52, 52)
                                   | None | Orner | Command |
                                   Conv20_5 input: [None, 32, 32, 66]
Conv20 serput: [None, 32, 32, 66]
                          No.b. prematerior, 5 input. (Nov., 12, 13, 64)
(No.b.Nematerior sutput. (Nov., 12, 13, 64)
                                  minutes | Imper | Olean, 32, 32, 60]
Arthreties respect | Olean, 32, 32, 60]
                          mor_proling20_2 input (None; 12.10, 60)
Mentholog20 insigns (None; 16, 16, 60)
                          Brapose, 2 Impair (Name, 16, 16, 60)
Despose Instage (Name, 16, 16, 60)
                         Com/26 Super (None, 16 16, 60)
Com/20 Super (None, 16 16, 120)
                beth semulation of laper (None, 16 16 129)
Beth Normalization output (None, 16 16 129)
                     activation of lingue: [Nose, 16, 36, 128]
Activation serger: [Nose, 16, 36, 128]
                         cont20_7 legal (Flore, 16, 16, 120)
Cont2D seigns (Flore, 16, 16, 120)
                heick_normalisation_T legen (None, 14, 14, 120)
Balab/Normalisation output (None, 14, 14, 120)
                     animation_7 input: [None, 56, 56, 125]
Schivation meigat: [None, 56, 56, 125]
            mac_pusing20_3 input | (Nonc, 16, 16, 130) |
MostNoding20 inspite | (Nonc, 6, 6, 130)
                 Bropout, 5 Impro: (News, 6, 6, 129)
| Dropout Output (News, 6, 6, 129)
                 OsmSt_6 Input (Nonc, 6, 6, 126)
Cam2D Output (Nonc, 6, 6, 126)
       bask-constitution_6 input (Now, 6, 6, 26)
(Nak-Nossalization surput (Now, 6, 6, 26)
                militation_X legal (Nons, 3, 3, 250)
Activation coaput (Nons, 5, 5, 250)
                 core 20_8 | Inquit | (Nove, 8, 8, 290)
| Core 20 | Inquit | (Nove, 8, 8, 290)
       hath_considering. I leps (Soc. 5, 5, 20)
(SachSonsiderine super (Soc. 5, 5, 20)
              schooles, 9 legen: (New, 8, 6, 254)
Animation coaper: (New, 8, 8, 254)
          Ostr 20, presspore in part (Nonc. 6, 6, 250)
Cont 20 Transpore integer (Nonc. 16, 16, 130)
dropout_4 imput (Noon, 16, 16, 250)
Dropout output (Noon, 16, 16, 250)
                 100736_50 (epst: 150ms, 3i, 3i, 250)
Chard D colput: (50ms, 3i, 3i, 13i)
            archiverine_EO (input: [Noor, 36, 36, 125]
Antirolium unique: [Noor, 36, 36, 125]
                     bezh,nomelizeler, II. leper Oleer, IG 15, 120;
BezhNomelizeler ouper Oleer, IG 16, 120;
                     scirution III input: (Store, 16, 36, 136)
Accirution output: (Store, 16, 36, 136)
                   condit transport | input | (None, H, H, 129)
| Condit transport | coput | (None, H, H, 50)
          Snopost_3 Impat (None, 12, 13, 139)
Diopost instgat (None, 12, 13, 139)
                       hat pendinto II inpt | Nos. II, II, 61 |
Bat Nendinto | sept | Nos. II, II, 61
                                minutine_EE input (None, EE, EE, 60)
Activation output (None, EE, EE, 60)
                              1000734_50000pccc_2 | Septic | Orlows, 32, 32, 60;
Cont 2017000pccc | Indignal | Orlows, 64, 64, 50;
                     Empres, 6 Impet (Force, 64, 64, 66)
Despress reciput (Force, 64, 64, 66)
                                  activation 34 input (None, 64, 64, 32)
Activation surput (None, 64, 64, 32)
                                            con/20_25 input [Now, 64, 64, 32)
Con/20 insput [Now, 64, 64, 32)
                                     hald-permittation_II input. [None, 64, 64, 22]
Bald-Normalisation output. [None, 64, 64, 22]
                                           antinosism_33 Imperi (Olean, 64, 64, 10)
Autinosism coapus (Olean, 64, 64, 10)
                                         81904,7 lapor Olino, 126, 126, 32)
Dropou output Olino, 126, 126, 32)
                                                                      coards_36 input: [Nose,138,138,35]
Coard3 seque: [Nose,138,138,15]
                                                             hath_nematistics_30 input (Now, 128, 128, 30)
SkithNematistics surput (Now, 128, 128, 30)
```

| MCNv66m,17 | Imper | Orient 128,126,160 |
| Arthrelin | Imper | Orient 128,126,160 |
| Orient 138,138,161 |
| Orient 138,138,181 |
| Or

```
[101]: | #Train model-----
    nbatch_size=128
    nepochs=200
    history = model.fit(X_train,Y_train,batch_size=nbatch_size,
                 epochs=nepochs, validation_split=0.2, shuffle=True,
                max_queue_size=32,workers=4,use_multiprocessing=True,
                )
   Epoch 1/200
   0.3560 - jacard_coef: 0.0937 - val_loss: 0.8787 - val_accuracy: 0.1291 -
   val_jacard_coef: 0.0720
   Epoch 2/200
   0.4166 - jacard_coef: 0.0838 - val_loss: 0.9006 - val_accuracy: 0.0789 -
   val jacard coef: 0.0788
   Epoch 3/200
   0.4976 - jacard_coef: 0.0785 - val_loss: 0.9140 - val_accuracy: 0.0749 -
   val_jacard_coef: 0.0777
   Epoch 4/200
   0.5952 - jacard_coef: 0.1011 - val_loss: 0.9098 - val_accuracy: 0.0751 -
   val_jacard_coef: 0.0762
   Epoch 5/200
   0.6928 - jacard_coef: 0.1392 - val_loss: 0.9156 - val_accuracy: 0.0753 -
   val jacard coef: 0.0769
   Epoch 6/200
   0.7597 - jacard_coef: 0.1559 - val_loss: 0.9163 - val_accuracy: 0.0762 -
   val_jacard_coef: 0.0785
   Epoch 7/200
   0.7702 - jacard_coef: 0.1627 - val_loss: 0.9153 - val_accuracy: 0.0778 -
   val_jacard_coef: 0.0805
   Epoch 8/200
   0.7679 - jacard_coef: 0.1221 - val_loss: 0.9200 - val_accuracy: 0.0782 -
   val_jacard_coef: 0.0781
   Epoch 9/200
   0.7809 - jacard coef: 0.1383 - val loss: 0.9182 - val accuracy: 0.0835 -
   val jacard coef: 0.0790
```

Epoch 10/200

```
0.7891 - jacard_coef: 0.1568 - val_loss: 0.9121 - val_accuracy: 0.1073 -
val_jacard_coef: 0.0763
Epoch 11/200
0.7891 - jacard_coef: 0.1879 - val_loss: 0.9026 - val_accuracy: 0.1521 -
val_jacard_coef: 0.0644
Epoch 12/200
0.7797 - jacard_coef: 0.1033 - val_loss: 0.8930 - val_accuracy: 0.1880 -
val_jacard_coef: 0.0670
Epoch 13/200
0.7771 - jacard_coef: 0.0942 - val_loss: 0.8998 - val_accuracy: 0.1636 -
val_jacard_coef: 0.0821
Epoch 14/200
0.8003 - jacard_coef: 0.1663 - val_loss: 0.9198 - val_accuracy: 0.1029 -
val_jacard_coef: 0.0784
Epoch 15/200
0.8193 - jacard_coef: 0.1041 - val_loss: 0.9237 - val_accuracy: 0.0835 -
val_jacard_coef: 0.0760
Epoch 16/200
0.8307 - jacard_coef: 0.1230 - val_loss: 0.9229 - val_accuracy: 0.0939 -
val_jacard_coef: 0.0765
Epoch 17/200
0.8429 - jacard_coef: 0.1475 - val_loss: 0.9184 - val_accuracy: 0.1409 -
val_jacard_coef: 0.0795
Epoch 18/200
0.8549 - jacard_coef: 0.1417 - val_loss: 0.8994 - val_accuracy: 0.2829 -
val jacard coef: 0.0909
Epoch 19/200
0.8562 - jacard_coef: 0.1817 - val_loss: 0.8845 - val_accuracy: 0.3986 -
val_jacard_coef: 0.0988
Epoch 20/200
0.8531 - jacard_coef: 0.1532 - val_loss: 0.8944 - val_accuracy: 0.3495 -
val_jacard_coef: 0.0944
Epoch 21/200
0.8609 - jacard_coef: 0.1239 - val_loss: 0.9016 - val_accuracy: 0.3003 -
val_jacard_coef: 0.0908
Epoch 22/200
```

```
0.8638 - jacard_coef: 0.1580 - val_loss: 0.9051 - val_accuracy: 0.2743 -
val_jacard_coef: 0.0889
Epoch 23/200
0.8687 - jacard_coef: 0.2130 - val_loss: 0.9078 - val_accuracy: 0.2512 -
val jacard coef: 0.0871
Epoch 24/200
0.8679 - jacard_coef: 0.1577 - val_loss: 0.9029 - val_accuracy: 0.2985 -
val_jacard_coef: 0.0906
Epoch 25/200
0.8659 - jacard_coef: 0.1194 - val_loss: 0.8927 - val_accuracy: 0.3785 -
val_jacard_coef: 0.0981
Epoch 26/200
0.8715 - jacard_coef: 0.1426 - val_loss: 0.8945 - val_accuracy: 0.3744 -
val_jacard_coef: 0.0969
Epoch 27/200
0.8779 - jacard_coef: 0.1419 - val_loss: 0.9040 - val_accuracy: 0.3040 -
val_jacard_coef: 0.0901
Epoch 28/200
0.8822 - jacard_coef: 0.2184 - val_loss: 0.9095 - val_accuracy: 0.2503 -
val_jacard_coef: 0.0862
Epoch 29/200
0.8851 - jacard_coef: 0.2239 - val_loss: 0.9191 - val_accuracy: 0.1405 -
val_jacard_coef: 0.0795
Epoch 30/200
0.8877 - jacard_coef: 0.2136 - val_loss: 0.9238 - val_accuracy: 0.0841 -
val jacard coef: 0.0759
Epoch 31/200
0.8848 - jacard_coef: 0.1317 - val_loss: 0.9233 - val_accuracy: 0.0902 -
val_jacard_coef: 0.0763
Epoch 32/200
0.8840 - jacard_coef: 0.1515 - val_loss: 0.9140 - val_accuracy: 0.1899 -
val_jacard_coef: 0.0835
Epoch 33/200
0.8838 - jacard_coef: 0.2213 - val_loss: 0.8854 - val_accuracy: 0.4163 -
val_jacard_coef: 0.1049
Epoch 34/200
```

```
0.8843 - jacard_coef: 0.2335 - val_loss: 0.8779 - val_accuracy: 0.4585 -
val_jacard_coef: 0.1099
Epoch 35/200
0.8902 - jacard_coef: 0.1427 - val_loss: 0.8812 - val_accuracy: 0.4411 -
val jacard coef: 0.1073
Epoch 36/200
0.8992 - jacard_coef: 0.1917 - val_loss: 0.8898 - val_accuracy: 0.3908 -
val_jacard_coef: 0.1013
Epoch 37/200
0.9096 - jacard_coef: 0.2535 - val_loss: 0.9100 - val_accuracy: 0.2320 -
val_jacard_coef: 0.0866
Epoch 38/200
0.9136 - jacard_coef: 0.1594 - val_loss: 0.9196 - val_accuracy: 0.1343 -
val_jacard_coef: 0.0793
Epoch 39/200
0.9100 - jacard_coef: 0.1687 - val_loss: 0.9204 - val_accuracy: 0.1238 -
val_jacard_coef: 0.0786
Epoch 40/200
0.9073 - jacard_coef: 0.2076 - val_loss: 0.9207 - val_accuracy: 0.1198 -
val_jacard_coef: 0.0784
Epoch 41/200
0.9054 - jacard_coef: 0.2225 - val_loss: 0.9218 - val_accuracy: 0.1070 -
val_jacard_coef: 0.0775
Epoch 42/200
0.9039 - jacard_coef: 0.1805 - val_loss: 0.9220 - val_accuracy: 0.1039 -
val jacard coef: 0.0774
Epoch 43/200
0.9017 - jacard_coef: 0.2183 - val_loss: 0.9209 - val_accuracy: 0.1163 -
val_jacard_coef: 0.0782
Epoch 44/200
0.9038 - jacard_coef: 0.2013 - val_loss: 0.9182 - val_accuracy: 0.1442 -
val_jacard_coef: 0.0802
Epoch 45/200
0.9078 - jacard_coef: 0.2330 - val_loss: 0.9108 - val_accuracy: 0.2143 -
val_jacard_coef: 0.0857
Epoch 46/200
```

```
0.9068 - jacard_coef: 0.1527 - val_loss: 0.8908 - val_accuracy: 0.3740 -
val_jacard_coef: 0.1000
Epoch 47/200
0.9052 - jacard_coef: 0.1764 - val_loss: 0.8904 - val_accuracy: 0.3783 -
val_jacard_coef: 0.1004
Epoch 48/200
0.9135 - jacard_coef: 0.1786 - val_loss: 0.9026 - val_accuracy: 0.2884 -
val_jacard_coef: 0.0915
Epoch 49/200
0.9170 - jacard_coef: 0.1990 - val_loss: 0.9129 - val_accuracy: 0.1992 -
val_jacard_coef: 0.0841
Epoch 50/200
0.9166 - jacard_coef: 0.1987 - val_loss: 0.9164 - val_accuracy: 0.1666 -
val_jacard_coef: 0.0817
Epoch 51/200
0.9181 - jacard_coef: 0.2404 - val_loss: 0.9163 - val_accuracy: 0.1692 -
val_jacard_coef: 0.0819
Epoch 52/200
0.9182 - jacard_coef: 0.1801 - val_loss: 0.9151 - val_accuracy: 0.1826 -
val_jacard_coef: 0.0828
Epoch 53/200
0.9157 - jacard_coef: 0.2046 - val_loss: 0.9119 - val_accuracy: 0.2142 -
val_jacard_coef: 0.0852
Epoch 54/200
0.9189 - jacard_coef: 0.2471 - val_loss: 0.9120 - val_accuracy: 0.2131 -
val jacard coef: 0.0850
Epoch 55/200
0.9217 - jacard_coef: 0.2245 - val_loss: 0.9188 - val_accuracy: 0.1391 -
val_jacard_coef: 0.0796
Epoch 56/200
0.9204 - jacard_coef: 0.2055 - val_loss: 0.9213 - val_accuracy: 0.1092 -
val_jacard_coef: 0.0777
Epoch 57/200
0.9186 - jacard_coef: 0.2064 - val_loss: 0.9211 - val_accuracy: 0.1108 -
val_jacard_coef: 0.0778
Epoch 58/200
```

```
0.9180 - jacard_coef: 0.2507 - val_loss: 0.9189 - val_accuracy: 0.1338 -
val_jacard_coef: 0.0795
Epoch 59/200
0.9163 - jacard_coef: 0.2900 - val_loss: 0.9148 - val_accuracy: 0.1753 -
val jacard coef: 0.0825
Epoch 60/200
0.9088 - jacard_coef: 0.2161 - val_loss: 0.9078 - val_accuracy: 0.2395 -
val_jacard_coef: 0.0876
Epoch 61/200
0.9039 - jacard_coef: 0.1988 - val_loss: 0.9035 - val_accuracy: 0.2771 -
val_jacard_coef: 0.0908
Epoch 62/200
0.9055 - jacard_coef: 0.2474 - val_loss: 0.9018 - val_accuracy: 0.2929 -
val_jacard_coef: 0.0921
Epoch 63/200
0.9096 - jacard_coef: 0.2006 - val_loss: 0.8986 - val_accuracy: 0.3202 -
val_jacard_coef: 0.0944
Epoch 64/200
0.9129 - jacard_coef: 0.2916 - val_loss: 0.8974 - val_accuracy: 0.3296 -
val_jacard_coef: 0.0952
Epoch 65/200
0.9163 - jacard_coef: 0.2174 - val_loss: 0.8953 - val_accuracy: 0.3427 -
val_jacard_coef: 0.0966
Epoch 66/200
0.9199 - jacard_coef: 0.2969 - val_loss: 0.8925 - val_accuracy: 0.3606 -
val jacard coef: 0.0986
Epoch 67/200
0.9215 - jacard_coef: 0.1965 - val_loss: 0.8909 - val_accuracy: 0.3709 -
val_jacard_coef: 0.0997
Epoch 68/200
0.9232 - jacard_coef: 0.2594 - val_loss: 0.8789 - val_accuracy: 0.4421 -
val_jacard_coef: 0.1078
Epoch 69/200
0.9233 - jacard_coef: 0.2327 - val_loss: 0.8540 - val_accuracy: 0.5535 -
val_jacard_coef: 0.1239
Epoch 70/200
```

```
0.9207 - jacard_coef: 0.1522 - val_loss: 0.8274 - val_accuracy: 0.6428 -
val_jacard_coef: 0.1388
Epoch 71/200
0.9196 - jacard_coef: 0.1907 - val_loss: 0.8107 - val_accuracy: 0.6836 -
val jacard coef: 0.1482
Epoch 72/200
0.9224 - jacard_coef: 0.1562 - val_loss: 0.8067 - val_accuracy: 0.6900 -
val_jacard_coef: 0.1508
Epoch 73/200
0.9270 - jacard_coef: 0.2329 - val_loss: 0.8098 - val_accuracy: 0.6819 -
val_jacard_coef: 0.1494
Epoch 74/200
0.9279 - jacard_coef: 0.2020 - val_loss: 0.8169 - val_accuracy: 0.6669 -
val_jacard_coef: 0.1449
Epoch 75/200
0.9265 - jacard_coef: 0.1686 - val_loss: 0.8250 - val_accuracy: 0.6511 -
val_jacard_coef: 0.1391
Epoch 76/200
0.9259 - jacard_coef: 0.2121 - val_loss: 0.8367 - val_accuracy: 0.6210 -
val_jacard_coef: 0.1321
Epoch 77/200
0.9248 - jacard_coef: 0.2397 - val_loss: 0.8453 - val_accuracy: 0.5912 -
val_jacard_coef: 0.1283
Epoch 78/200
0.9262 - jacard_coef: 0.2817 - val_loss: 0.8453 - val_accuracy: 0.5863 -
val jacard coef: 0.1297
Epoch 79/200
0.9284 - jacard_coef: 0.2685 - val_loss: 0.8397 - val_accuracy: 0.6001 -
val_jacard_coef: 0.1348
Epoch 80/200
0.9252 - jacard_coef: 0.2667 - val_loss: 0.8400 - val_accuracy: 0.5985 -
val_jacard_coef: 0.1356
Epoch 81/200
0.9229 - jacard_coef: 0.2789 - val_loss: 0.8481 - val_accuracy: 0.5737 -
val_jacard_coef: 0.1307
Epoch 82/200
```

```
0.9231 - jacard_coef: 0.3120 - val_loss: 0.8564 - val_accuracy: 0.5436 -
val_jacard_coef: 0.1255
Epoch 83/200
0.9227 - jacard_coef: 0.2278 - val_loss: 0.8820 - val_accuracy: 0.4252 -
val jacard coef: 0.1078
Epoch 84/200
0.9215 - jacard_coef: 0.3187 - val_loss: 0.9110 - val_accuracy: 0.2146 -
val_jacard_coef: 0.0860
Epoch 85/200
0.9147 - jacard_coef: 0.3250 - val_loss: 0.9174 - val_accuracy: 0.1524 -
val_jacard_coef: 0.0809
Epoch 86/200
0.9111 - jacard_coef: 0.2980 - val_loss: 0.9139 - val_accuracy: 0.1875 -
val_jacard_coef: 0.0837
Epoch 87/200
0.9124 - jacard_coef: 0.2703 - val_loss: 0.9012 - val_accuracy: 0.2967 -
val_jacard_coef: 0.0937
Epoch 88/200
0.9147 - jacard_coef: 0.2229 - val_loss: 0.8868 - val_accuracy: 0.3957 -
val_jacard_coef: 0.1041
Epoch 89/200
0.9174 - jacard_coef: 0.3106 - val_loss: 0.8705 - val_accuracy: 0.4841 -
val_jacard_coef: 0.1152
Epoch 90/200
0.9211 - jacard_coef: 0.2827 - val_loss: 0.8550 - val_accuracy: 0.5471 -
val jacard coef: 0.1250
Epoch 91/200
0.9235 - jacard_coef: 0.2817 - val_loss: 0.8419 - val_accuracy: 0.5905 -
val_jacard_coef: 0.1329
Epoch 92/200
0.9262 - jacard_coef: 0.3212 - val_loss: 0.8388 - val_accuracy: 0.5998 -
val_jacard_coef: 0.1350
Epoch 93/200
0.9266 - jacard_coef: 0.3034 - val_loss: 0.8490 - val_accuracy: 0.5651 -
val_jacard_coef: 0.1293
Epoch 94/200
```

```
0.9252 - jacard_coef: 0.3097 - val_loss: 0.8605 - val_accuracy: 0.5178 -
val_jacard_coef: 0.1223
Epoch 95/200
0.9249 - jacard_coef: 0.2023 - val_loss: 0.8685 - val_accuracy: 0.4807 -
val jacard coef: 0.1170
Epoch 96/200
0.9234 - jacard_coef: 0.2875 - val_loss: 0.8710 - val_accuracy: 0.4685 -
val_jacard_coef: 0.1155
Epoch 97/200
0.9232 - jacard_coef: 0.2217 - val_loss: 0.8734 - val_accuracy: 0.4589 -
val_jacard_coef: 0.1144
Epoch 98/200
0.9238 - jacard_coef: 0.2619 - val_loss: 0.8774 - val_accuracy: 0.4414 -
val_jacard_coef: 0.1116
Epoch 99/200
0.9211 - jacard_coef: 0.3137 - val_loss: 0.8811 - val_accuracy: 0.4218 -
val_jacard_coef: 0.1085
Epoch 100/200
0.9234 - jacard_coef: 0.3024 - val_loss: 0.8798 - val_accuracy: 0.4270 -
val_jacard_coef: 0.1088
Epoch 101/200
0.9284 - jacard_coef: 0.2489 - val_loss: 0.8633 - val_accuracy: 0.5051 -
val_jacard_coef: 0.1201
Epoch 102/200
0.9300 - jacard_coef: 0.2119 - val_loss: 0.8357 - val_accuracy: 0.6011 -
val jacard coef: 0.1392
Epoch 103/200
0.9302 - jacard_coef: 0.2713 - val_loss: 0.8155 - val_accuracy: 0.6542 -
val_jacard_coef: 0.1518
Epoch 104/200
0.9311 - jacard_coef: 0.3346 - val_loss: 0.8110 - val_accuracy: 0.6636 -
val_jacard_coef: 0.1542
Epoch 105/200
0.9323 - jacard_coef: 0.2663 - val_loss: 0.8143 - val_accuracy: 0.6559 -
val_jacard_coef: 0.1521
Epoch 106/200
```

```
0.9319 - jacard_coef: 0.3352 - val_loss: 0.8283 - val_accuracy: 0.6224 -
val_jacard_coef: 0.1428
Epoch 107/200
0.9293 - jacard_coef: 0.3521 - val_loss: 0.8441 - val_accuracy: 0.5768 -
val jacard coef: 0.1326
Epoch 108/200
0.9222 - jacard_coef: 0.2858 - val_loss: 0.8555 - val_accuracy: 0.5360 -
val_jacard_coef: 0.1256
Epoch 109/200
0.9147 - jacard_coef: 0.2085 - val_loss: 0.8631 - val_accuracy: 0.5052 -
val_jacard_coef: 0.1207
Epoch 110/200
0.9141 - jacard_coef: 0.2736 - val_loss: 0.8628 - val_accuracy: 0.5060 -
val_jacard_coef: 0.1217
Epoch 111/200
0.9185 - jacard_coef: 0.2380 - val_loss: 0.8540 - val_accuracy: 0.5405 -
val_jacard_coef: 0.1289
Epoch 112/200
0.9215 - jacard_coef: 0.3077 - val_loss: 0.8416 - val_accuracy: 0.5826 -
val_jacard_coef: 0.1384
Epoch 113/200
0.9246 - jacard_coef: 0.3507 - val_loss: 0.8429 - val_accuracy: 0.5805 -
val_jacard_coef: 0.1375
Epoch 114/200
0.9279 - jacard_coef: 0.2874 - val_loss: 0.8598 - val_accuracy: 0.5203 -
val jacard coef: 0.1250
Epoch 115/200
0.9255 - jacard_coef: 0.3268 - val_loss: 0.8795 - val_accuracy: 0.4229 -
val_jacard_coef: 0.1104
Epoch 116/200
0.9259 - jacard_coef: 0.3313 - val_loss: 0.8945 - val_accuracy: 0.3329 -
val_jacard_coef: 0.0990
Epoch 117/200
0.9263 - jacard_coef: 0.3363 - val_loss: 0.9016 - val_accuracy: 0.2840 -
val_jacard_coef: 0.0935
Epoch 118/200
```

```
0.9264 - jacard_coef: 0.3079 - val_loss: 0.9039 - val_accuracy: 0.2658 -
val_jacard_coef: 0.0916
Epoch 119/200
0.9287 - jacard_coef: 0.2971 - val_loss: 0.9019 - val_accuracy: 0.2816 -
val jacard coef: 0.0931
Epoch 120/200
0.9307 - jacard_coef: 0.2771 - val_loss: 0.8998 - val_accuracy: 0.2976 -
val_jacard_coef: 0.0947
Epoch 121/200
0.9316 - jacard_coef: 0.3475 - val_loss: 0.9005 - val_accuracy: 0.2923 -
val_jacard_coef: 0.0941
Epoch 122/200
0.9301 - jacard_coef: 0.2895 - val_loss: 0.9001 - val_accuracy: 0.2928 -
val_jacard_coef: 0.0943
Epoch 123/200
0.9292 - jacard_coef: 0.3293 - val_loss: 0.8994 - val_accuracy: 0.2944 -
val_jacard_coef: 0.0946
Epoch 124/200
0.9303 - jacard_coef: 0.2770 - val_loss: 0.8948 - val_accuracy: 0.3241 -
val_jacard_coef: 0.0982
Epoch 125/200
0.9308 - jacard_coef: 0.3263 - val_loss: 0.8715 - val_accuracy: 0.4534 -
val_jacard_coef: 0.1157
Epoch 126/200
0.9317 - jacard_coef: 0.2402 - val_loss: 0.8090 - val_accuracy: 0.6596 -
val jacard coef: 0.1598
Epoch 127/200
0.9321 - jacard_coef: 0.2765 - val_loss: 0.7370 - val_accuracy: 0.7842 -
val_jacard_coef: 0.2043
Epoch 128/200
0.9291 - jacard_coef: 0.2535 - val_loss: 0.7060 - val_accuracy: 0.8191 -
val_jacard_coef: 0.2204
Epoch 129/200
0.9285 - jacard_coef: 0.2498 - val_loss: 0.7204 - val_accuracy: 0.8027 -
val_jacard_coef: 0.2122
Epoch 130/200
```

```
0.9299 - jacard_coef: 0.2897 - val_loss: 0.7628 - val_accuracy: 0.7518 -
val_jacard_coef: 0.1873
Epoch 131/200
0.9301 - jacard_coef: 0.2582 - val_loss: 0.8025 - val_accuracy: 0.6905 -
val jacard coef: 0.1616
Epoch 132/200
0.9308 - jacard_coef: 0.3106 - val_loss: 0.8265 - val_accuracy: 0.6418 -
val_jacard_coef: 0.1455
Epoch 133/200
0.9314 - jacard_coef: 0.2810 - val_loss: 0.8396 - val_accuracy: 0.6087 -
val_jacard_coef: 0.1367
Epoch 134/200
0.9307 - jacard_coef: 0.2953 - val_loss: 0.8397 - val_accuracy: 0.6133 -
val_jacard_coef: 0.1365
Epoch 135/200
0.9303 - jacard_coef: 0.3317 - val_loss: 0.8270 - val_accuracy: 0.6450 -
val_jacard_coef: 0.1457
Epoch 136/200
0.9321 - jacard_coef: 0.3345 - val_loss: 0.8061 - val_accuracy: 0.6799 -
val_jacard_coef: 0.1606
Epoch 137/200
0.9322 - jacard_coef: 0.2807 - val_loss: 0.7923 - val_accuracy: 0.6988 -
val_jacard_coef: 0.1701
Epoch 138/200
0.9303 - jacard_coef: 0.2924 - val_loss: 0.7914 - val_accuracy: 0.7003 -
val jacard coef: 0.1707
Epoch 139/200
0.9282 - jacard_coef: 0.3113 - val_loss: 0.7869 - val_accuracy: 0.7081 -
val_jacard_coef: 0.1738
Epoch 140/200
0.9295 - jacard_coef: 0.2601 - val_loss: 0.7845 - val_accuracy: 0.7110 -
val_jacard_coef: 0.1751
Epoch 141/200
0.9327 - jacard_coef: 0.3516 - val_loss: 0.7825 - val_accuracy: 0.7144 -
val_jacard_coef: 0.1755
Epoch 142/200
```

```
0.9341 - jacard_coef: 0.2959 - val_loss: 0.7807 - val_accuracy: 0.7153 -
val_jacard_coef: 0.1759
Epoch 143/200
0.9362 - jacard_coef: 0.3123 - val_loss: 0.7774 - val_accuracy: 0.7212 -
val jacard coef: 0.1772
Epoch 144/200
0.9395 - jacard_coef: 0.3109 - val_loss: 0.7902 - val_accuracy: 0.7076 -
val_jacard_coef: 0.1681
Epoch 145/200
0.9400 - jacard_coef: 0.2588 - val_loss: 0.8146 - val_accuracy: 0.6690 -
val_jacard_coef: 0.1522
Epoch 146/200
0.9395 - jacard_coef: 0.2640 - val_loss: 0.8198 - val_accuracy: 0.6578 -
val_jacard_coef: 0.1490
Epoch 147/200
0.9403 - jacard_coef: 0.3222 - val_loss: 0.8014 - val_accuracy: 0.6903 -
val_jacard_coef: 0.1607
Epoch 148/200
0.9423 - jacard_coef: 0.3349 - val_loss: 0.7953 - val_accuracy: 0.6994 -
val_jacard_coef: 0.1652
Epoch 149/200
0.9408 - jacard_coef: 0.2679 - val_loss: 0.7992 - val_accuracy: 0.6932 -
val_jacard_coef: 0.1638
Epoch 150/200
0.9422 - jacard_coef: 0.3333 - val_loss: 0.8054 - val_accuracy: 0.6837 -
val jacard coef: 0.1606
Epoch 151/200
0.9402 - jacard_coef: 0.3866 - val_loss: 0.8208 - val_accuracy: 0.6513 -
val_jacard_coef: 0.1516
Epoch 152/200
0.9340 - jacard_coef: 0.2835 - val_loss: 0.8309 - val_accuracy: 0.6186 -
val_jacard_coef: 0.1459
Epoch 153/200
0.9311 - jacard_coef: 0.3651 - val_loss: 0.8418 - val_accuracy: 0.5791 -
val_jacard_coef: 0.1390
Epoch 154/200
```

```
0.9349 - jacard_coef: 0.3447 - val_loss: 0.8514 - val_accuracy: 0.5454 -
val_jacard_coef: 0.1321
Epoch 155/200
0.9318 - jacard_coef: 0.3144 - val_loss: 0.8575 - val_accuracy: 0.5243 -
val jacard coef: 0.1275
Epoch 156/200
0.9339 - jacard_coef: 0.2587 - val_loss: 0.8564 - val_accuracy: 0.5324 -
val_jacard_coef: 0.1283
Epoch 157/200
0.9303 - jacard_coef: 0.2960 - val_loss: 0.8452 - val_accuracy: 0.5743 -
val_jacard_coef: 0.1363
Epoch 158/200
0.9283 - jacard_coef: 0.3285 - val_loss: 0.8357 - val_accuracy: 0.6003 -
val_jacard_coef: 0.1432
Epoch 159/200
0.9292 - jacard_coef: 0.3473 - val_loss: 0.8340 - val_accuracy: 0.6006 -
val_jacard_coef: 0.1446
Epoch 160/200
0.9289 - jacard_coef: 0.2616 - val_loss: 0.8261 - val_accuracy: 0.6204 -
val_jacard_coef: 0.1503
Epoch 161/200
0.9281 - jacard_coef: 0.3397 - val_loss: 0.8151 - val_accuracy: 0.6491 -
val_jacard_coef: 0.1584
Epoch 162/200
0.9267 - jacard_coef: 0.2899 - val_loss: 0.8003 - val_accuracy: 0.6822 -
val jacard coef: 0.1689
Epoch 163/200
0.9266 - jacard_coef: 0.3010 - val_loss: 0.7813 - val_accuracy: 0.7158 -
val_jacard_coef: 0.1817
Epoch 164/200
0.9284 - jacard_coef: 0.2679 - val_loss: 0.7637 - val_accuracy: 0.7416 -
val_jacard_coef: 0.1925
Epoch 165/200
0.9295 - jacard_coef: 0.3749 - val_loss: 0.7518 - val_accuracy: 0.7554 -
val_jacard_coef: 0.1991
Epoch 166/200
```

```
0.9315 - jacard_coef: 0.3107 - val_loss: 0.7566 - val_accuracy: 0.7470 -
val_jacard_coef: 0.1958
Epoch 167/200
0.9318 - jacard_coef: 0.2915 - val_loss: 0.7752 - val_accuracy: 0.7195 -
val jacard coef: 0.1839
Epoch 168/200
0.9328 - jacard_coef: 0.3456 - val_loss: 0.7887 - val_accuracy: 0.6959 -
val_jacard_coef: 0.1749
Epoch 169/200
0.9332 - jacard_coef: 0.2015 - val_loss: 0.7854 - val_accuracy: 0.7007 -
val_jacard_coef: 0.1771
Epoch 170/200
0.9340 - jacard_coef: 0.3792 - val_loss: 0.7727 - val_accuracy: 0.7196 -
val_jacard_coef: 0.1850
Epoch 171/200
0.9373 - jacard_coef: 0.2640 - val_loss: 0.7562 - val_accuracy: 0.7487 -
val_jacard_coef: 0.1956
Epoch 172/200
0.9406 - jacard_coef: 0.3404 - val_loss: 0.7438 - val_accuracy: 0.7785 -
val_jacard_coef: 0.2028
Epoch 173/200
0.9406 - jacard_coef: 0.3186 - val_loss: 0.7753 - val_accuracy: 0.7665 -
val_jacard_coef: 0.1801
Epoch 174/200
0.9363 - jacard_coef: 0.3621 - val_loss: 0.7988 - val_accuracy: 0.7215 -
val jacard coef: 0.1659
Epoch 175/200
0.9286 - jacard_coef: 0.3614 - val_loss: 0.8079 - val_accuracy: 0.6736 -
val_jacard_coef: 0.1625
Epoch 176/200
0.9248 - jacard_coef: 0.2867 - val_loss: 0.8075 - val_accuracy: 0.6670 -
val_jacard_coef: 0.1639
Epoch 177/200
0.9284 - jacard_coef: 0.2619 - val_loss: 0.7883 - val_accuracy: 0.7027 -
val_jacard_coef: 0.1776
Epoch 178/200
```

```
0.9321 - jacard_coef: 0.3782 - val_loss: 0.7779 - val_accuracy: 0.7203 -
val_jacard_coef: 0.1843
Epoch 179/200
0.9315 - jacard_coef: 0.3855 - val_loss: 0.7976 - val_accuracy: 0.6880 -
val jacard coef: 0.1706
Epoch 180/200
0.9315 - jacard_coef: 0.3917 - val_loss: 0.8187 - val_accuracy: 0.6426 -
val_jacard_coef: 0.1562
Epoch 181/200
0.9308 - jacard_coef: 0.3050 - val_loss: 0.8335 - val_accuracy: 0.6003 -
val_jacard_coef: 0.1456
Epoch 182/200
0.9356 - jacard_coef: 0.2778 - val_loss: 0.8390 - val_accuracy: 0.5839 -
val_jacard_coef: 0.1415
Epoch 183/200
0.9373 - jacard_coef: 0.2421 - val_loss: 0.8318 - val_accuracy: 0.6055 -
val_jacard_coef: 0.1468
Epoch 184/200
0.9354 - jacard_coef: 0.2126 - val_loss: 0.8211 - val_accuracy: 0.6345 -
val_jacard_coef: 0.1550
Epoch 185/200
0.9348 - jacard_coef: 0.3301 - val_loss: 0.8084 - val_accuracy: 0.6621 -
val_jacard_coef: 0.1644
Epoch 186/200
0.9381 - jacard_coef: 0.4091 - val_loss: 0.7980 - val_accuracy: 0.6813 -
val jacard coef: 0.1719
Epoch 187/200
0.9406 - jacard_coef: 0.3890 - val_loss: 0.7985 - val_accuracy: 0.6783 -
val_jacard_coef: 0.1720
Epoch 188/200
0.9411 - jacard_coef: 0.3946 - val_loss: 0.8115 - val_accuracy: 0.6504 -
val_jacard_coef: 0.1631
Epoch 189/200
0.9428 - jacard_coef: 0.3511 - val_loss: 0.8294 - val_accuracy: 0.6059 -
val_jacard_coef: 0.1500
Epoch 190/200
```

```
0.9441 - jacard_coef: 0.2785 - val_loss: 0.8332 - val_accuracy: 0.5952 -
   val_jacard_coef: 0.1469
   Epoch 191/200
   0.9439 - jacard_coef: 0.3350 - val_loss: 0.8153 - val_accuracy: 0.6416 -
   val jacard coef: 0.1594
   Epoch 192/200
   0.9451 - jacard_coef: 0.3373 - val_loss: 0.7862 - val_accuracy: 0.7030 -
   val_jacard_coef: 0.1795
   Epoch 193/200
   0.9447 - jacard_coef: 0.2994 - val_loss: 0.7568 - val_accuracy: 0.7540 -
   val_jacard_coef: 0.1981
   Epoch 194/200
   0.9436 - jacard_coef: 0.3280 - val_loss: 0.7657 - val_accuracy: 0.7397 -
   val_jacard_coef: 0.1923
   Epoch 195/200
   0.9446 - jacard_coef: 0.2895 - val_loss: 0.8043 - val_accuracy: 0.6703 -
   val_jacard_coef: 0.1670
   Epoch 196/200
   0.9466 - jacard_coef: 0.3836 - val_loss: 0.8300 - val_accuracy: 0.6075 -
   val_jacard_coef: 0.1488
   Epoch 197/200
   0.9453 - jacard_coef: 0.3147 - val_loss: 0.8444 - val_accuracy: 0.5654 -
   val_jacard_coef: 0.1386
   Epoch 198/200
   0.9454 - jacard_coef: 0.3207 - val_loss: 0.8380 - val_accuracy: 0.5854 -
   val jacard coef: 0.1434
   Epoch 199/200
   0.9481 - jacard_coef: 0.4450 - val_loss: 0.8121 - val_accuracy: 0.6519 -
   val_jacard_coef: 0.1619
   Epoch 200/200
   0.9469 - jacard_coef: 0.3586 - val_loss: 0.7742 - val_accuracy: 0.7246 -
   val_jacard_coef: 0.1880
[102]: df_result = pd.DataFrame(history.history)
    df_result
```

```
[102]:
               loss accuracy jacard_coef val_loss val_accuracy val_jacard_coef
      0
           0.872040 0.356049
                                  0.093717
                                            0.878686
                                                          0.129052
                                                                           0.071997
      1
           0.846515 0.416591
                                  0.083771 0.900601
                                                          0.078904
                                                                           0.078783
      2
           0.826054 0.497650
                                  0.078493 0.914008
                                                          0.074944
                                                                           0.077734
      3
           0.807635 0.595213
                                  0.101147 0.909849
                                                          0.075099
                                                                           0.076188
           0.786400 0.692813
                                  0.139161 0.915594
                                                          0.075293
                                                                           0.076855
      . .
      195 0.394641 0.946577
                                  0.383552 0.830006
                                                          0.607496
                                                                          0.148772
      196 0.396441 0.945278
                                  0.314745 0.844410
                                                          0.565446
                                                                           0.138572
      197 0.389689 0.945366
                                  0.320742 0.838025
                                                          0.585351
                                                                           0.143395
      198 0.370472 0.948130
                                  0.445005 0.812102
                                                          0.651905
                                                                           0.161890
      199 0.372572 0.946875
                                  0.358567 0.774213
                                                          0.724639
                                                                           0.188048
      [200 rows x 6 columns]
```

### 5 Visualize the model predictions

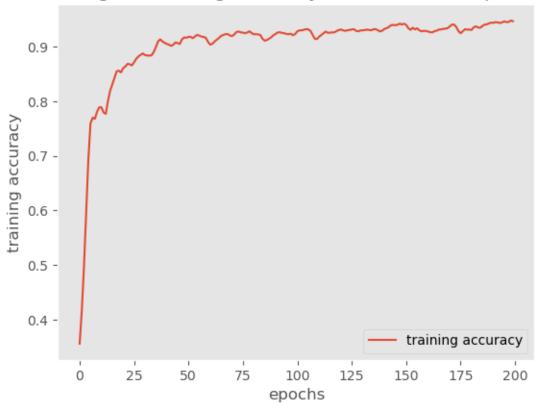
```
[103]: # Plotting loss change over epochs-----
       nrange=nepochs
       x = [i for i in range(nrange)]
       plt.plot(x,history.history['loss'])
       plt.title('change in loss over epochs')
       plt.legend(['training_loss'])
       plt.xlabel('epochs')
       plt.ylabel('loss')
       #plt.axis('off')
       plt.grid(None)
       plt.show()
       plt.tight_layout()
       # Plotting accuracy change over epochs-----
       x = [i for i in range(nrange)]
       plt.plot(x,history.history['accuracy'])
       plt.title('change in training accuracy coefitient over epochs')
       plt.legend(['training accuracy'])
       plt.xlabel('epochs')
       plt.ylabel('training accuracy')
       plt.grid(None)
       plt.show()
       plt.tight_layout()
       # Plotting accuracy change over epochs----
       x = [i for i in range(nrange)]
       plt.plot(x,history.history['jacard_coef'])
       plt.title('change in jacard_coef coefitient over epochs')
       plt.legend(['jacard_coef'])
```

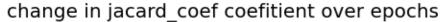
```
plt.xlabel('epochs')
plt.ylabel('jacard_coef')
plt.grid(None)
plt.show()
plt.tight_layout()
```

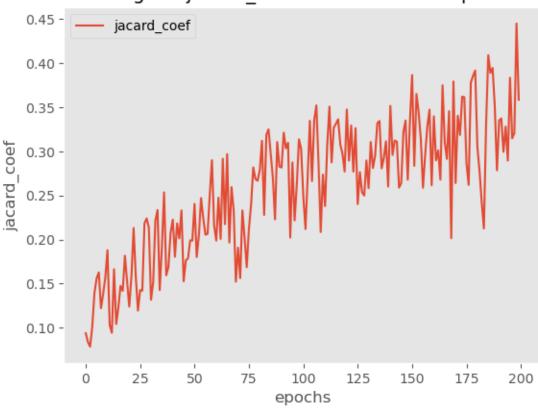
## change in loss over epochs











#### <Figure size 640x480 with 0 Axes>

```
[104]: # Creating predictions on our test set-----
predictions = model.predict(X_test)

# create predictes mask-----

def create_mask(predictions,input_shape=(W,H,1)):
    mask = np.zeros(input_shape)
    mask[predictions>0.5] = 1
    return mask
```

#### 2/2 [=======] - 2s 233ms/step

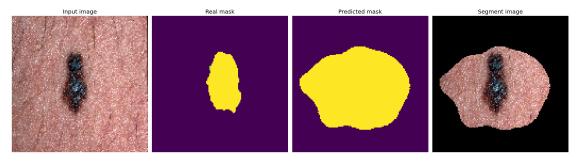
```
[105]: # Ploting results for one image

def plot_results_for_one_sample(sample_index):

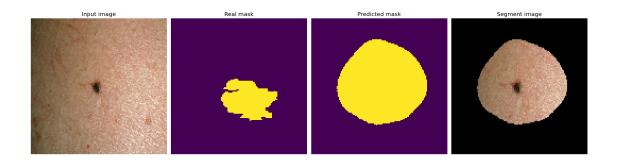
    mask = create_mask(predictions[sample_index])
    fig = plt.figure(figsize=(20,20))
```

```
#image
fig.add_subplot(1,4,1)
plt.title('Input image')
plt.imshow(X_test[sample_index])
plt.axis('off')
plt.grid(None)
#mask
fig.add_subplot(1,4,2)
plt.title('Real mask')
plt.imshow(Y_test[sample_index])
plt.axis('off')
plt.grid(None)
#Predicted mask
fig.add_subplot(1,4,3)
plt.title('Predicted mask')
plt.imshow(mask)
plt.axis('off')
plt.grid(None)
#Segment
fig.add_subplot(1,4,4)
plt.title("Segment image")
plt.imshow(X_test[sample_index]*mask)
plt.grid(None)
plt.axis('off')
fig.tight_layout()
```

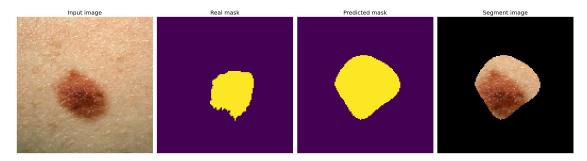
# [106]: #Show predicted result----plot\_results\_for\_one\_sample(0)



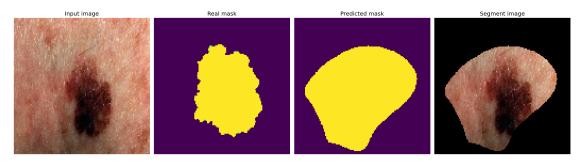
```
[107]: #Show predicted result-----
plot_results_for_one_sample(1)
```



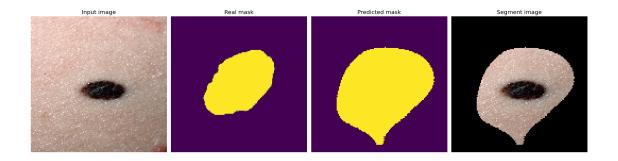
[108]: #Show predicted result----plot\_results\_for\_one\_sample(2)



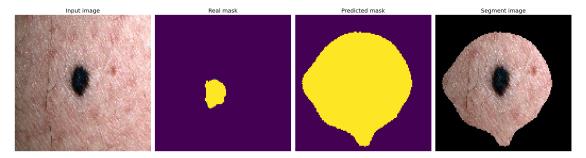
[109]: #Show predicted result----plot\_results\_for\_one\_sample(3)



[110]: #Show predicted result----plot\_results\_for\_one\_sample(4)



# [111]: #Show predicted result----plot\_results\_for\_one\_sample(5)



[]: