

# Constant Declaration and Module Imports

In [1]:

```
# import modules
import numpy as np
import pandas as pd
import sys
import os
import random
import warnings
import time

import matplotlib.pyplot as plt

import collections

from skimage.io import imread, imshow
from skimage.transform import resize
from skimage.morphology import label

from keras.preprocessing.image import ImageDataGenerator
from keras.models import Model, load_model
from keras.layers import Input
from keras.layers.convolutional import Conv2D, Conv2DTranspose
from keras.layers.core import Dropout, Lambda
from keras.layers.pooling import MaxPooling2D
from keras.layers.merge import concatenate
from keras.callbacks import EarlyStopping, ModelCheckpoint
from keras import backend as K

from sklearn.model_selection import train_test_split

import tensorflow as tf

from tqdm import tqdm

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list
the files in the input directory
from subprocess import check_output
print(check_output(["ls", "input"]).decode("utf8"))

# Any results you write to the current directory are saved as output.

/home/ubuntu/anaconda3/envs/py35/lib/python3.5/site-packages/h5py/___
init__.py:36: FutureWarning: Conversion of the second argument of is
subtype from `float` to `np.floating` is deprecated. In future, it
will be treated as `np.float64 == np.dtype(float).type`.
    from ._conv import register_converters as _register_converters
Using TensorFlow backend.

stage1_test
stage1_train
```

## Define constant (image size and images paths)

In [2]:

```
# Set some parameters
IMG_WIDTH = 256
IMG_HEIGHT = 256
IMG_DEPTH = 3
TRAIN_PATH = 'input/stage1_train/'
TEST_PATH = 'input/stage1_test/'

# set the seed for the random module. DO NOT ERASE.
warnings.filterwarnings('ignore', category=UserWarning, module='skimage')
```

## Data Download

In [3]:

```
Xtrain = []
Xtest = []

# Create the ids of all training images and all the testing images.
try:
    train_ids = next(os.walk(TRAIN_PATH))[1]
except StopIteration:
    print('the ids of all training images created. There are {}'.format(len(train_ids)))

try:
    test_ids = next(os.walk(TEST_PATH))[1]
except StopIteration:
    print('the ids of all testing images created')

# Create placeholder for images.
# I am using list because the shape of the images is unknown at this stage.
# Arrays require the declaration of dimensions.
X_train = []
X_test = []

# function that converts file name (string) into an image
def str_to_img(path, id_):
    img = imread(path + id_ + '/images/' + id_ + '.png')[:, :, :IMG_DEPTH]
    return img

# function that creates a bar chart from a counter
def barchart(counter, title):
    labels, values = zip(*counter.items())
    incr = int(max(values)/20)
    indexes = np.arange(len(labels))
    width = 0.75
    fig, ax = plt.subplots()
    plt.bar(indexes, values, width)
    plt.xticks(indexes, labels, rotation=45, fontsize=10)
    plt.title(title)
    plt.xlabel('image size', fontsize=10)
    plt.ylabel('number of images')
    for i, values in enumerate(counter.values()):
        ax.text(i - width*0.2, values+incr, str(values), color='blue', fontweight='bold')
    plt.show()

def print_table(counter, train_vs_test):
    pd_data_list = [list(counter.keys()), list(counter.values())]
    pd_data = pd.DataFrame(np.array(pd_data_list).T, columns=['Size', 'Count'])
    pd_data['Count'] = pd_data['Count'].apply(pd.to_numeric)
    # using 'display' instead of 'print' will use jupyter rich display logic.
    display(pd_data)
    print('The total number of '+train_vs_test+' images is: {}'.format(pd_data['Count'].sum()))

print('Generating training images ...')
for n, id_ in tqdm(enumerate(train_ids), total=len(train_ids)):
    X_train.append(str_to_img(TRAIN_PATH, id_))

print('Generating test images ...')
for n, id_ in tqdm(enumerate(test_ids), total=len(test_ids)):
    X_test.append(str_to_img(TEST_PATH, id_))
```

```
print('Calculating the dimensions of the training and test images...')
# Analyze size of all training images and testing images
train_ids_size = [img.shape for img in X_train]
test_ids_size = [img.shape for img in X_test]
counter_train = collections.Counter(train_ids_size)
counter_test = collections.Counter(test_ids_size)

print('----> Visualizing data through histograms ...')
barchart(counter_train, "Count of images per size (training set)")
barchart(counter_test, "Count of images per size (test set)")

print('----> Visualizing data through tables ...')
print_table(counter_train, 'training')
print_table(counter_test, 'test')
```

1%| | 8/670 [00:00<00:10, 63.43it/s]

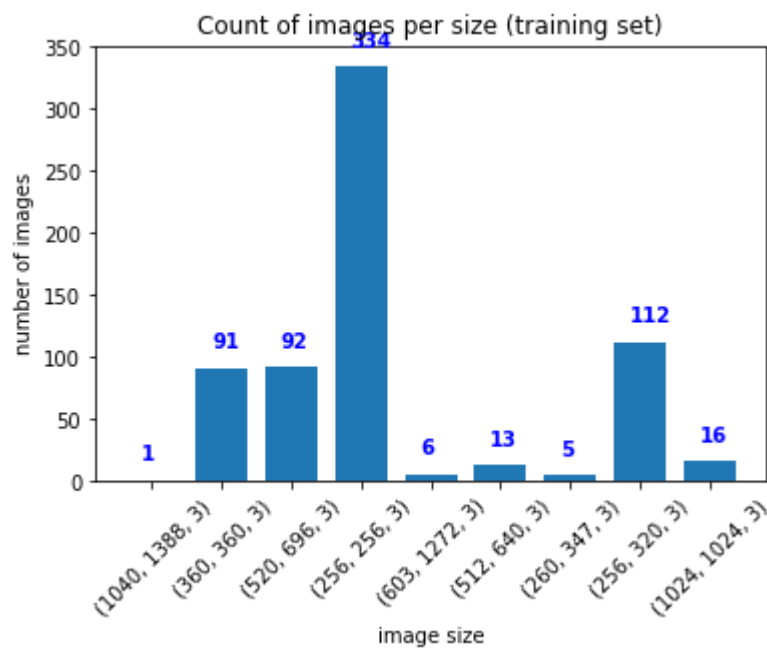
Generating training images ...

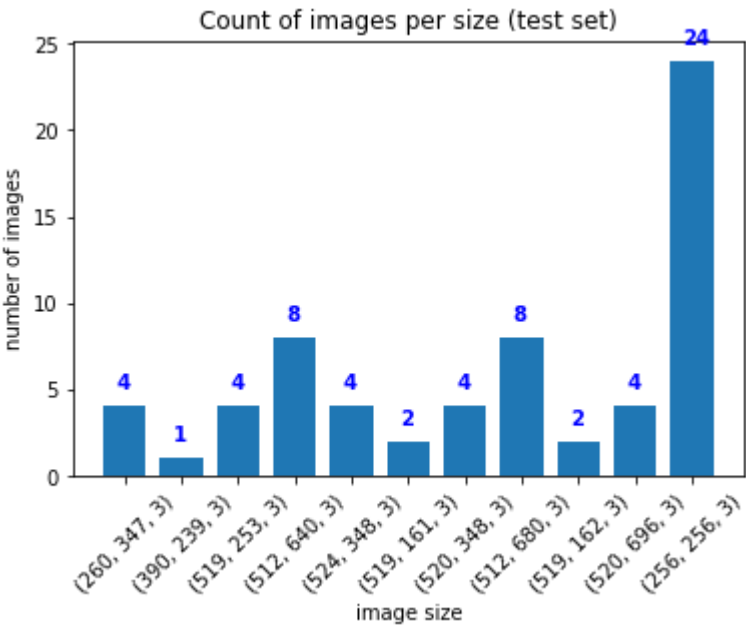
100%|██████████| 670/670 [00:03<00:00, 189.38it/s]  
26%|███| 17/65 [00:00<00:00, 161.63it/s]

Generating test images ...

100%|██████████| 65/65 [00:00<00:00, 163.68it/s]

Calculating the dimensions of the training and test images...  
----> Visualizing data through histograms ...





----> Visualizing data through tables ...

|   | Size            | Count |
|---|-----------------|-------|
| 0 | (1040, 1388, 3) | 1     |
| 1 | (360, 360, 3)   | 91    |
| 2 | (520, 696, 3)   | 92    |
| 3 | (256, 256, 3)   | 334   |
| 4 | (603, 1272, 3)  | 6     |
| 5 | (512, 640, 3)   | 13    |
| 6 | (260, 347, 3)   | 5     |
| 7 | (256, 320, 3)   | 112   |
| 8 | (1024, 1024, 3) | 16    |

The total number of training images is: 670

|    | Size          | Count |
|----|---------------|-------|
| 0  | (260, 347, 3) | 4     |
| 1  | (390, 239, 3) | 1     |
| 2  | (519, 253, 3) | 4     |
| 3  | (512, 640, 3) | 8     |
| 4  | (524, 348, 3) | 4     |
| 5  | (519, 161, 3) | 2     |
| 6  | (520, 348, 3) | 4     |
| 7  | (512, 680, 3) | 8     |
| 8  | (519, 162, 3) | 2     |
| 9  | (520, 696, 3) | 4     |
| 10 | (256, 256, 3) | 24    |

The total number of test images is: 65

In [4]:

```
# Create placeholder for images
X_train = np.zeros((len(train_ids), IMG_HEIGHT, IMG_WIDTH, IMG_DEPTH), dtype=np.float32)
Y_train = np.zeros((len(train_ids), IMG_HEIGHT, IMG_WIDTH, 1), dtype=np.float32)

# Flush the buffer to see the progress in real time
sys.stdout.flush()

print('Getting and resizing training images ... ')
for n, id_ in tqdm(enumerate(train_ids), total=len(train_ids)):
    path = TRAIN_PATH + id_
    img = imread(path + '/images/' + id_ + '.png')[:, :, :IMG_DEPTH]
    img = resize(img, (IMG_HEIGHT, IMG_WIDTH), mode='constant', preserve_range=True)
    # normalize the images to float between 0 and 1
    X_train[n] = img / 255
    mask = np.zeros((IMG_HEIGHT, IMG_WIDTH, 1), dtype=np.bool)
    for mask_file in next(os.walk(path + '/masks/'))[2]:
        mask_ = imread(path + '/masks/' + mask_file)
        mask_ = np.expand_dims(resize(mask_, (IMG_HEIGHT, IMG_WIDTH), mode='constant',
                                     preserve_range=True), axis=-1)
        mask = np.maximum(mask, mask_)
    # normalize the images to float between 0 and 1
    Y_train[n] = mask / 255

# Get and resize test images
X_test = np.zeros((len(test_ids), IMG_HEIGHT, IMG_WIDTH, IMG_DEPTH), dtype=np.float32)
sizes_test = []
print('Getting and resizing test images ... ')
sys.stdout.flush()
for n, id_ in tqdm(enumerate(test_ids), total=len(test_ids)):
    path = TEST_PATH + id_
    img = imread(path + '/images/' + id_ + '.png')[:, :, :IMG_DEPTH]
    sizes_test.append([img.shape[0], img.shape[1]])
    img = resize(img, (IMG_HEIGHT, IMG_WIDTH), mode='constant', preserve_range=True)
    # normalize the images to float between 0 and 1
    X_test[n] = img / 255
```

```
0%|          | 0/670 [00:00<?, ?it/s]

Getting and resizing training images ...

100%|██████████| 670/670 [01:56<00:00, 5.77it/s]

Getting and resizing test images ...

100%|██████████| 65/65 [00:00<00:00, 69.09it/s]
```

### Visualize an image and its mask



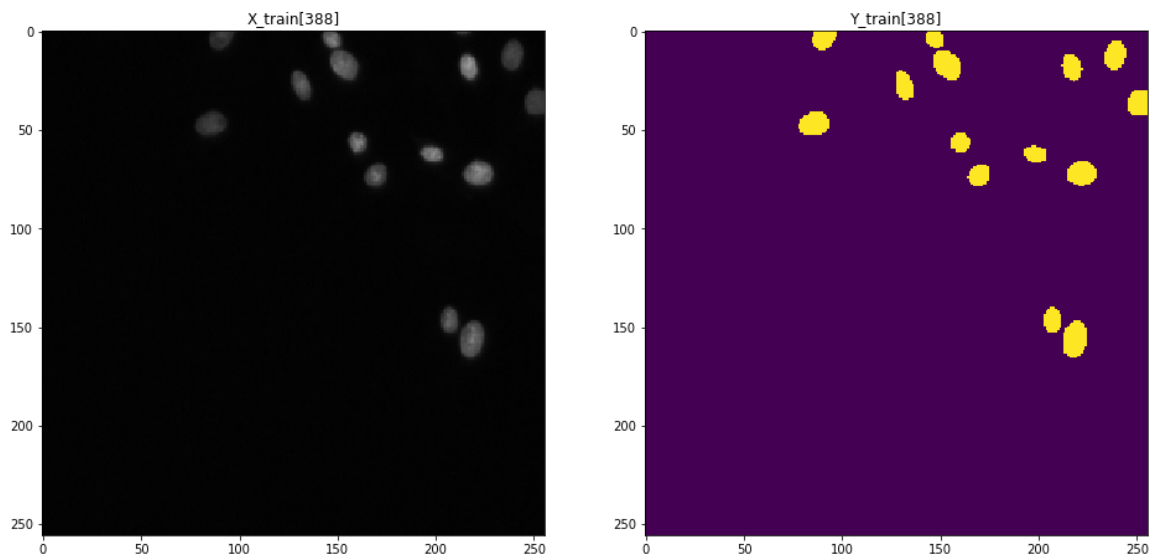
In [5]:

```
# check the shape of X_train (the first four lines). Each image should have a size of (256, 256, 3).
print(X_train[1:5].shape)

(4, 256, 256, 3)
```

In [6]:

```
# Check some data
ind = random.randint(0, len(train_ids))
# Change the size of the plot
plt.rcParams["figure.figsize"] = [16,9]
# Draw two sets of images (train and test)
_, axarr = plt.subplots(1,2)
axarr[0].imshow(X_train[ind])
axarr[0].set_title("X_train["+str(ind)+"]")
axarr[1].imshow(np.squeeze(Y_train[ind]))
axarr[1].set_title("Y_train["+str(ind)+"]")
plt.show()
```



We can see that the nuclei are clearly segmented in the training data.

### Augment training data

In [7]:

```
# define batch size (used in the generator and during training)
batch_size = 16

# define a helper function generator() to create the data generators
def generator():
    # define constants
    validation_split = 0.1
    seed_split = 42

    # start the clock
    start = time.time()

    # create Test/Train validation split
    X_train_split, X_test_split, Y_train_split, Y_test_split = train_test_split(
X_train,
Y_train,
train_size=1-validation_split,
test_size=validation_split,
random_state=seed_split)

    data_gen_args = dict(shear_range=0.2,
                        zoom_range=0.2,
                        horizontal_flip=True,
                        vertical_flip=True,
                        width_shift_range=0.2,
                        height_shift_range=0.2,
                        rotation_range=90,
                        fill_mode='reflect')

    train_image_datagen = ImageDataGenerator(**data_gen_args)
    train_mask_datagen = ImageDataGenerator(**data_gen_args)
    test_image_datagen = ImageDataGenerator()
    test_mask_datagen = ImageDataGenerator()

    # compute quantities required for featurewise normalization
    # (std, mean, and principal components if ZCA whitening is applied)
    # Provide the same seed and keyword arguments to the fit and flow methods
    # (source: https://keras.io/preprocessing/image/)
    train_image_datagen.fit(X_train_split, augment=True, seed=42)
    train_mask_datagen.fit(Y_train_split, augment=True, seed=42)
    test_image_datagen.fit(X_train_split, augment=True, seed=42)
    test_mask_datagen.fit(Y_train_split, augment=True, seed=42)

    train_image_generator = train_image_datagen.flow(X_train_split, seed=42, batch_size=batch_size, shuffle=True)
    train_mask_generator = train_mask_datagen.flow(Y_train_split, seed=42, batch_size=batch_size, shuffle=True)
    test_image_generator = test_image_datagen.flow(X_test_split, seed=42, batch_size=batch_size, shuffle=True)
    test_mask_generator = test_mask_datagen.flow(Y_test_split, seed=42, batch_size=batch_size, shuffle=True)

    train_generator = zip(train_image_generator, train_mask_generator)
    test_generator = zip(test_image_generator, test_mask_generator)
```

```

end = time.time()
delta = end - start

print('Data was augmented in {:6.2f} seconds'.format(delta))
return (train_generator, test_generator)

```

In [8]:

```

# helper function to visualize augmented data
def visualize_augmented_data():
    for X_batch in train_image_datagen.flow(X_train, batch_size=9):
        # create a grid of 3x3 images
        for i in range(0, 9):
            plt.subplot(330 + 1 + i)
            plt.imshow(X_batch[i], cmap=plt.get_cmap('gray'))
        # show the plot
        plt.show()
        break

    print('-'*50)

    for y_batch in train_mask_datagen.flow(Y_train, batch_size=9):
        # create a grid of 3x3 images
        for i in range(0, 9):
            plt.subplot(330 + 1 + i)
            plt.imshow(y_batch[i].reshape(IMG_WIDTH, IMG_HEIGHT), cmap=plt.get_cm
ap('gray'))
        # show the plot
        plt.show()
        break

```

## Define Keras Metric

In [9]:

```

# Define IoU metric
def mean_iou(y_true, y_pred):
    prec = []
    for t in np.arange(0.5, 1.0, 0.05):
        y_pred_ = tf.to_int32(y_pred > t)
        score, up_opt = tf.metrics.mean_iou(y_true, y_pred_, 2)
        K.get_session().run(tf.local_variables_initializer())
        with tf.control_dependencies([up_opt]):
            score = tf.identity(score)
        prec.append(score)
    return K.mean(K.stack(prec), axis=0)

```

## Build The Benchmark

In [10]:

```
# Build the benchmark model
def build_benchmark_initial():
    inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_DEPTH))
    c1 = Conv2D(16, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(inputs)
    c1 = Dropout(0.1)(c1)
    c1 = Conv2D(16, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(c1)
    p1 = MaxPooling2D((2, 2))(c1)
    u9 = Conv2DTranspose(16, (2, 2), strides=(2, 2), padding='same')(p1)
    outputs = Conv2D(1, (1, 1), activation='sigmoid')(c1)
    model_benchmark = Model(inputs=[inputs], outputs=[outputs])
    model_benchmark.compile(optimizer='adam', loss='binary_crossentropy', metrics=[mean_iou])
    model_benchmark.summary()
    return model_benchmark
```

In [11]:

```
# Build the benchmark model
def build_benchmark():
    inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_DEPTH))
    c1 = Conv2D(16, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(inputs)
    c1 = Dropout(0.1)(c1)
    c1 = Conv2D(16, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(c1)
    outputs = Conv2D(1, (1, 1), activation='sigmoid')(c1)
    model_benchmark = Model(inputs=[inputs], outputs=[outputs])
    model_benchmark.compile(optimizer='adam', loss='binary_crossentropy', metrics=[mean_iou])
    model_benchmark.summary()
    return model_benchmark
```

## Create a helper function to train any model

In [12]:

```
def train(model, model_file):
    earlystopper = EarlyStopping(patience=5, verbose=1)
    checkpointer = ModelCheckpoint(model_file, verbose=1, save_best_only=True)
    results = model.fit(X_train, Y_train, validation_split=0.1, batch_size=16, epochs=50,
                        callbacks=[earlystopper, checkpointer])
    # summarize history for metrics
    plt.plot(results.history['loss'])
    plt.plot(results.history['val_loss'])
    plt.plot(results.history['mean_iou'])
    plt.plot(results.history['val_mean_iou'])
    plt.title('model accuracy')
    plt.ylabel('metric')
    plt.xlabel('epoch')
    plt.legend(['train_loss', 'test_loss', 'train_mean_iou', 'test_mean_iou'], loc='upper left')
    plt.show()
```

**Train benchmark model**

In [13]:

```
# create initial benchmark model
model_benchmark = build_benchmark_initial()
# fit model
start = time.time()
train(model_benchmark, 'model-benchmark_initial_50.h5')
end = time.time()
delta = end - start
print('The benchmark model was trained in {:.0f} seconds.'.format(delta))
```

| Layer (type)         | Output Shape         | Param # |
|----------------------|----------------------|---------|
| input_1 (InputLayer) | (None, 256, 256, 3)  | 0       |
| conv2d_1 (Conv2D)    | (None, 256, 256, 16) | 448     |
| dropout_1 (Dropout)  | (None, 256, 256, 16) | 0       |
| conv2d_2 (Conv2D)    | (None, 256, 256, 16) | 2320    |
| conv2d_3 (Conv2D)    | (None, 256, 256, 1)  | 17      |

=====  
Total params: 2,785

Trainable params: 2,785

Non-trainable params: 0

=====  
Train on 603 samples, validate on 67 samples

Epoch 1/50

603/603 [=====] - 50s 84ms/step - loss: 0.5730 - mean\_iou: 0.4208 - val\_loss: 0.4893 - val\_mean\_iou: 0.4361

Epoch 00001: val\_loss improved from inf to 0.48927, saving model to model-benchmark\_initial\_50.h5

Epoch 2/50

603/603 [=====] - 48s 80ms/step - loss: 0.4233 - mean\_iou: 0.4449 - val\_loss: 0.3834 - val\_mean\_iou: 0.4541

Epoch 00002: val\_loss improved from 0.48927 to 0.38337, saving model to model-benchmark\_initial\_50.h5

Epoch 3/50

603/603 [=====] - 48s 79ms/step - loss: 0.3784 - mean\_iou: 0.4623 - val\_loss: 0.3708 - val\_mean\_iou: 0.4679

Epoch 00003: val\_loss improved from 0.38337 to 0.37080, saving model to model-benchmark\_initial\_50.h5

Epoch 4/50

603/603 [=====] - 48s 80ms/step - loss: 0.3644 - mean\_iou: 0.4708 - val\_loss: 0.3442 - val\_mean\_iou: 0.4738

Epoch 00004: val\_loss improved from 0.37080 to 0.34421, saving model to model-benchmark\_initial\_50.h5

Epoch 5/50

603/603 [=====] - 48s 80ms/step - loss: 0.3399 - mean\_iou: 0.4766 - val\_loss: 0.3147 - val\_mean\_iou: 0.4778

Epoch 00005: val\_loss improved from 0.34421 to 0.31471, saving model to model-benchmark\_initial\_50.h5

Epoch 6/50

603/603 [=====] - 48s 80ms/step - loss: 0.3062 - mean\_iou: 0.4794 - val\_loss: 0.2792 - val\_mean\_iou: 0.4805

Epoch 00006: val\_loss improved from 0.31471 to 0.27917, saving model to model-benchmark\_initial\_50.h5

Epoch 7/50

603/603 [=====] - 48s 80ms/step - loss: 0.2624 - mean\_iou: 0.4821 - val\_loss: 0.2517 - val\_mean\_iou: 0.4836

Epoch 00007: val\_loss improved from 0.27917 to 0.25174, saving model to model-benchmark\_initial\_50.h5

Epoch 8/50

603/603 [=====] - 48s 80ms/step - loss: 0.2  
284 - mean\_iou: 0.4864 - val\_loss: 0.2226 - val\_mean\_iou: 0.4901

Epoch 00008: val\_loss improved from 0.25174 to 0.22258, saving model  
to model-benchmark\_initial\_50.h5

Epoch 9/50

603/603 [=====] - 49s 81ms/step - loss: 0.2  
095 - mean\_iou: 0.4945 - val\_loss: 0.2020 - val\_mean\_iou: 0.4998

Epoch 00009: val\_loss improved from 0.22258 to 0.20202, saving model  
to model-benchmark\_initial\_50.h5

Epoch 10/50

603/603 [=====] - 48s 79ms/step - loss: 0.2  
021 - mean\_iou: 0.5049 - val\_loss: 0.2119 - val\_mean\_iou: 0.5103

Epoch 00010: val\_loss did not improve

Epoch 11/50

603/603 [=====] - 48s 79ms/step - loss: 0.1  
965 - mean\_iou: 0.5151 - val\_loss: 0.2010 - val\_mean\_iou: 0.5196

Epoch 00011: val\_loss improved from 0.20202 to 0.20099, saving model  
to model-benchmark\_initial\_50.h5

Epoch 12/50

603/603 [=====] - 47s 78ms/step - loss: 0.1  
945 - mean\_iou: 0.5245 - val\_loss: 0.2063 - val\_mean\_iou: 0.5291

Epoch 00012: val\_loss did not improve

Epoch 13/50

603/603 [=====] - 49s 81ms/step - loss: 0.1  
940 - mean\_iou: 0.5328 - val\_loss: 0.1989 - val\_mean\_iou: 0.5367

Epoch 00013: val\_loss improved from 0.20099 to 0.19893, saving model  
to model-benchmark\_initial\_50.h5

Epoch 14/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
907 - mean\_iou: 0.5407 - val\_loss: 0.1918 - val\_mean\_iou: 0.5441

Epoch 00014: val\_loss improved from 0.19893 to 0.19179, saving model  
to model-benchmark\_initial\_50.h5

Epoch 15/50

603/603 [=====] - 49s 81ms/step - loss: 0.1  
905 - mean\_iou: 0.5475 - val\_loss: 0.1942 - val\_mean\_iou: 0.5505

Epoch 00015: val\_loss did not improve

Epoch 16/50

603/603 [=====] - 48s 79ms/step - loss: 0.1  
886 - mean\_iou: 0.5536 - val\_loss: 0.1979 - val\_mean\_iou: 0.5563

Epoch 00016: val\_loss did not improve

Epoch 17/50

603/603 [=====] - 48s 79ms/step - loss: 0.1  
882 - mean\_iou: 0.5586 - val\_loss: 0.1969 - val\_mean\_iou: 0.5611

Epoch 00017: val\_loss did not improve

Epoch 18/50

603/603 [=====] - 47s 79ms/step - loss: 0.1  
891 - mean\_iou: 0.5638 - val\_loss: 0.1947 - val\_mean\_iou: 0.5656

Epoch 00018: val\_loss did not improve

Epoch 19/50

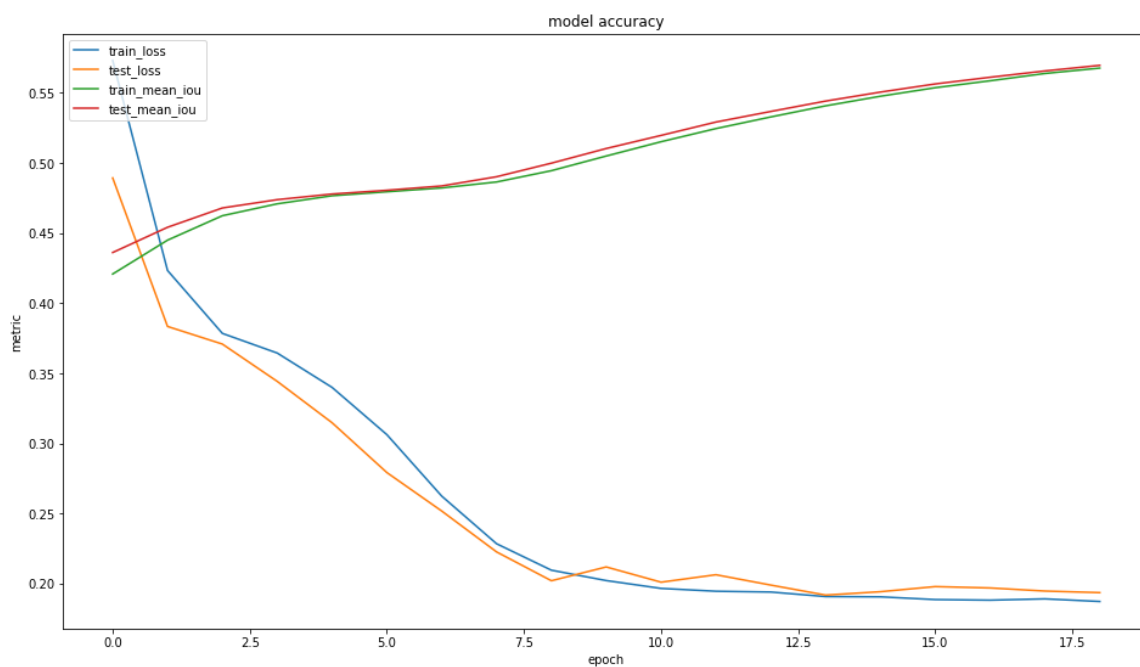
603/603 [=====] - 48s 79ms/step - loss: 0.1



872 - mean\_iou: 0.5676 - val\_loss: 0.1935 - val\_mean\_iou: 0.5696

Epoch 00019: val\_loss did not improve

Epoch 00019: early stopping



The benchmark model was trained in 916 seconds.

In [27]:

```
# create benchmark model
model_benchmark = build_benchmark()
# fit model
start = time.time()
train(model_benchmark, 'model-benchmark_50.h5')
end = time.time()
delta = end - start
print('The benchmark model was trained in {:.0f} seconds.'.format(delta))
```

| Layer (type)         | Output Shape         | Param # |
|----------------------|----------------------|---------|
| input_2 (InputLayer) | (None, 256, 256, 3)  | 0       |
| conv2d_20 (Conv2D)   | (None, 256, 256, 16) | 448     |
| dropout_10 (Dropout) | (None, 256, 256, 16) | 0       |
| conv2d_21 (Conv2D)   | (None, 256, 256, 16) | 2320    |
| conv2d_22 (Conv2D)   | (None, 256, 256, 1)  | 17      |

=====  
Total params: 2,785

Trainable params: 2,785

Non-trainable params: 0

=====  
Train on 603 samples, validate on 67 samples

Epoch 1/50

603/603 [=====] - 53s 89ms/step - loss: 0.6036 - mean\_iou: 0.4268 - val\_loss: 0.5359 - val\_mean\_iou: 0.4363

Epoch 00001: val\_loss improved from inf to 0.53587, saving model to model-benchmark\_50.h5

Epoch 2/50

603/603 [=====] - 48s 79ms/step - loss: 0.4568 - mean\_iou: 0.4361 - val\_loss: 0.3906 - val\_mean\_iou: 0.4378

Epoch 00002: val\_loss improved from 0.53587 to 0.39064, saving model to model-benchmark\_50.h5

Epoch 3/50

603/603 [=====] - 48s 80ms/step - loss: 0.3780 - mean\_iou: 0.4426 - val\_loss: 0.3562 - val\_mean\_iou: 0.4479

Epoch 00003: val\_loss improved from 0.39064 to 0.35625, saving model to model-benchmark\_50.h5

Epoch 4/50

603/603 [=====] - 48s 80ms/step - loss: 0.3503 - mean\_iou: 0.4524 - val\_loss: 0.3222 - val\_mean\_iou: 0.4566

Epoch 00004: val\_loss improved from 0.35625 to 0.32216, saving model to model-benchmark\_50.h5

Epoch 5/50

603/603 [=====] - 47s 78ms/step - loss: 0.3126 - mean\_iou: 0.4605 - val\_loss: 0.2856 - val\_mean\_iou: 0.4641

Epoch 00005: val\_loss improved from 0.32216 to 0.28558, saving model to model-benchmark\_50.h5

Epoch 6/50

603/603 [=====] - 48s 79ms/step - loss: 0.2621 - mean\_iou: 0.4680 - val\_loss: 0.2342 - val\_mean\_iou: 0.4719

Epoch 00006: val\_loss improved from 0.28558 to 0.23421, saving model to model-benchmark\_50.h5

Epoch 7/50

603/603 [=====] - 48s 80ms/step - loss: 0.2251 - mean\_iou: 0.4779 - val\_loss: 0.2141 - val\_mean\_iou: 0.4842

Epoch 00007: val\_loss improved from 0.23421 to 0.21412, saving model to model-benchmark\_50.h5

Epoch 8/50

603/603 [=====] - 48s 80ms/step - loss: 0.2  
059 - mean\_iou: 0.4911 - val\_loss: 0.2033 - val\_mean\_iou: 0.4979

Epoch 00008: val\_loss improved from 0.21412 to 0.20327, saving model  
to model-benchmark\_50.h5

Epoch 9/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
983 - mean\_iou: 0.5049 - val\_loss: 0.1977 - val\_mean\_iou: 0.5116

Epoch 00009: val\_loss improved from 0.20327 to 0.19770, saving model  
to model-benchmark\_50.h5

Epoch 10/50

603/603 [=====] - 48s 79ms/step - loss: 0.1  
944 - mean\_iou: 0.5176 - val\_loss: 0.1977 - val\_mean\_iou: 0.5233

Epoch 00010: val\_loss improved from 0.19770 to 0.19765, saving model  
to model-benchmark\_50.h5

Epoch 11/50

603/603 [=====] - 48s 79ms/step - loss: 0.1  
988 - mean\_iou: 0.5288 - val\_loss: 0.2064 - val\_mean\_iou: 0.5335

Epoch 00011: val\_loss did not improve

Epoch 12/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
961 - mean\_iou: 0.5386 - val\_loss: 0.1960 - val\_mean\_iou: 0.5426

Epoch 00012: val\_loss improved from 0.19765 to 0.19597, saving model  
to model-benchmark\_50.h5

Epoch 13/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
888 - mean\_iou: 0.5465 - val\_loss: 0.1953 - val\_mean\_iou: 0.5502

Epoch 00013: val\_loss improved from 0.19597 to 0.19529, saving model  
to model-benchmark\_50.h5

Epoch 14/50

603/603 [=====] - 49s 81ms/step - loss: 0.1  
881 - mean\_iou: 0.5538 - val\_loss: 0.1937 - val\_mean\_iou: 0.5569

Epoch 00014: val\_loss improved from 0.19529 to 0.19373, saving model  
to model-benchmark\_50.h5

Epoch 15/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
869 - mean\_iou: 0.5597 - val\_loss: 0.1963 - val\_mean\_iou: 0.5628

Epoch 00015: val\_loss did not improve

Epoch 16/50

603/603 [=====] - 48s 79ms/step - loss: 0.1  
870 - mean\_iou: 0.5651 - val\_loss: 0.1917 - val\_mean\_iou: 0.5676

Epoch 00016: val\_loss improved from 0.19373 to 0.19172, saving model  
to model-benchmark\_50.h5

Epoch 17/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
847 - mean\_iou: 0.5701 - val\_loss: 0.1929 - val\_mean\_iou: 0.5723

Epoch 00017: val\_loss did not improve

Epoch 18/50

603/603 [=====] - 48s 79ms/step - loss: 0.1  
856 - mean\_iou: 0.5743 - val\_loss: 0.1923 - val\_mean\_iou: 0.5763

Epoch 00018: val\_loss did not improve

Epoch 19/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
836 - mean\_iou: 0.5779 - val\_loss: 0.1927 - val\_mean\_iou: 0.5798

Epoch 00019: val\_loss did not improve

Epoch 20/50

603/603 [=====] - 48s 79ms/step - loss: 0.1  
824 - mean\_iou: 0.5816 - val\_loss: 0.1917 - val\_mean\_iou: 0.5832

Epoch 00020: val\_loss improved from 0.19172 to 0.19166, saving model  
to model-benchmark\_50.h5

Epoch 21/50

603/603 [=====] - 49s 81ms/step - loss: 0.1  
825 - mean\_iou: 0.5848 - val\_loss: 0.1976 - val\_mean\_iou: 0.5863

Epoch 00021: val\_loss did not improve

Epoch 22/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
813 - mean\_iou: 0.5877 - val\_loss: 0.1899 - val\_mean\_iou: 0.5891

Epoch 00022: val\_loss improved from 0.19166 to 0.18994, saving model  
to model-benchmark\_50.h5

Epoch 23/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
809 - mean\_iou: 0.5904 - val\_loss: 0.1985 - val\_mean\_iou: 0.5917

Epoch 00023: val\_loss did not improve

Epoch 24/50

603/603 [=====] - 48s 80ms/step - loss: 0.1  
821 - mean\_iou: 0.5930 - val\_loss: 0.1919 - val\_mean\_iou: 0.5941

Epoch 00024: val\_loss did not improve

Epoch 25/50

603/603 [=====] - 48s 79ms/step - loss: 0.1  
810 - mean\_iou: 0.5951 - val\_loss: 0.1902 - val\_mean\_iou: 0.5962

Epoch 00025: val\_loss did not improve

Epoch 26/50

603/603 [=====] - 49s 81ms/step - loss: 0.1  
803 - mean\_iou: 0.5973 - val\_loss: 0.1925 - val\_mean\_iou: 0.5984

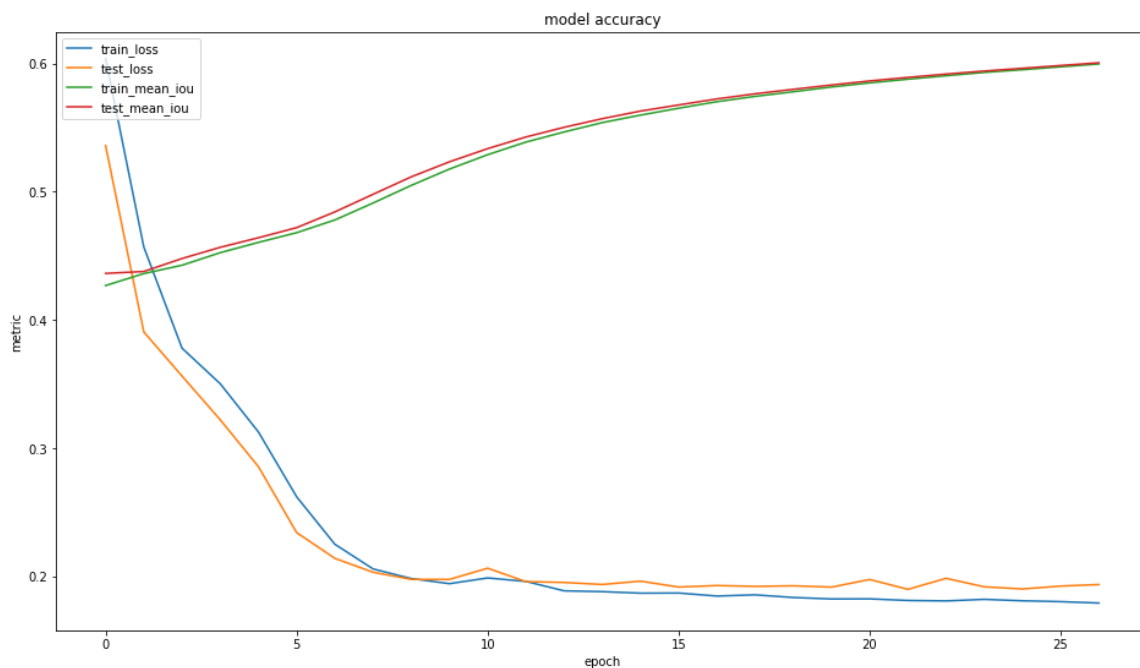
Epoch 00026: val\_loss did not improve

Epoch 27/50

603/603 [=====] - 49s 80ms/step - loss: 0.1  
793 - mean\_iou: 0.5996 - val\_loss: 0.1937 - val\_mean\_iou: 0.6005

Epoch 00027: val\_loss did not improve

Epoch 00027: early stopping



The benchmark model was trained in 1308 seconds.

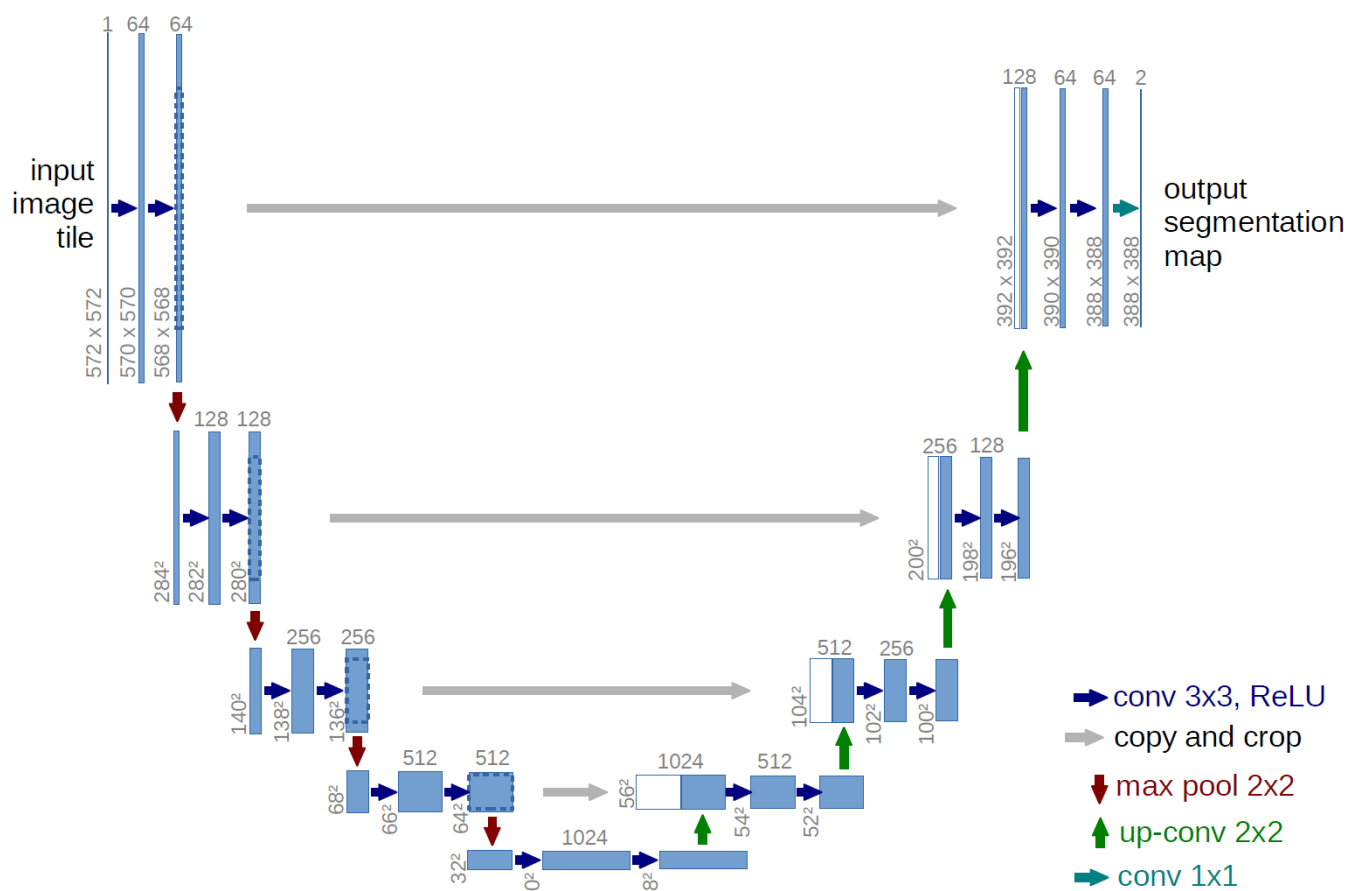
## Build The Neural Network

The Unet architecture (used by Olaf Ronneberger, Philipp Fischer, and Thomas Brox). Source:

<https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/u-net-architecture.png>

(<https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/u-net-architecture.png>)

Our network uses images which are twice as small.



In [11]:

```
# Build U-Net model
def u_net():
    inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_DEPTH))

    c1 = Conv2D(16, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(inputs)
    c1 = Dropout(0.1)(c1)
    c1 = Conv2D(16, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(c1)
    p1 = MaxPooling2D((2, 2))(c1)

    c2 = Conv2D(32, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(p1)
    c2 = Dropout(0.1)(c2)
    c2 = Conv2D(32, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(c2)
    p2 = MaxPooling2D((2, 2))(c2)

    c3 = Conv2D(64, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(p2)
    c3 = Dropout(0.2)(c3)
    c3 = Conv2D(64, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(c3)
    p3 = MaxPooling2D((2, 2))(c3)

    c4 = Conv2D(128, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(p3)
    c4 = Dropout(0.2)(c4)
    c4 = Conv2D(128, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(c4)
    p4 = MaxPooling2D(pool_size=(2, 2))(c4)

    c5 = Conv2D(256, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(p4)
    c5 = Dropout(0.3)(c5)
    c5 = Conv2D(256, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(c5)

    u6 = Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same')(c5)
    u6 = concatenate([u6, c4])
    c6 = Conv2D(128, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(u6)
    c6 = Dropout(0.2)(c6)
    c6 = Conv2D(128, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(c6)

    u7 = Conv2DTranspose(64, (2, 2), strides=(2, 2), padding='same')(c6)
    u7 = concatenate([u7, c3])
    c7 = Conv2D(64, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(u7)
    c7 = Dropout(0.2)(c7)
    c7 = Conv2D(64, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(c7)

    u8 = Conv2DTranspose(32, (2, 2), strides=(2, 2), padding='same')(c7)
    u8 = concatenate([u8, c2])
    c8 = Conv2D(32, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same')(u8)
```

```
c8 = Dropout(0.1) (c8)
c8 = Conv2D(32, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same') (c8)

u9 = Conv2DTranspose(16, (2, 2), strides=(2, 2), padding='same') (c8)
u9 = concatenate([u9, c1], axis=3)
c9 = Conv2D(16, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same') (u9)
c9 = Dropout(0.1) (c9)
c9 = Conv2D(16, (3, 3), activation='elu', kernel_initializer='he_normal', padding='same') (c9)

outputs = Conv2D(1, (1, 1), activation='sigmoid') (c9)

model = Model(inputs=[inputs], outputs=[outputs])
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=[mean_iou])
model.summary()
return model
```

### Training the model with the original data



In [31]:

```
# create model
model = u_net()
# Fit model without augmented data
start = time.time()
train(model, 'model-dsbow12018-50epochsF.h5')
end = time.time()
delta = end - start
print('The Unet model using the original data was trained in {:.6.2f}'.format(delta))

#earlystopper = EarlyStopping(patience=5, verbose=1)
#checkpointer = ModelCheckpoint('model-dsbow12018-50epochs.h5', verbose=1, save_
best_only=True)
#results = model.fit(X_train, Y_train, validation_split=0.1, batch_size=16, epoc
hs=50,
#                      callbacks=[earlystopper, chackpointer])
```

| Layer (type)<br>connected to                   | Output Shape         | Param # | Con |
|--|----------------------|---------|-----|
| input_11 (InputLayer)                          | (None, 256, 256, 3)  | 0       |     |
| conv2d_31 (Conv2D)<br>ut_11[0][0]              | (None, 256, 256, 16) | 448     | inp |
| dropout_11 (Dropout)<br>v2d_31[0][0]           | (None, 256, 256, 16) | 0       | con |
| conv2d_32 (Conv2D)<br>pout_11[0][0]            | (None, 256, 256, 16) | 2320    | dro |
| max_pooling2d_1 (MaxPooling2D)<br>v2d_32[0][0] | (None, 128, 128, 16) | 0       | con |
| conv2d_33 (Conv2D)<br>_pooling2d_1[0][0]       | (None, 128, 128, 32) | 4640    | max |
| dropout_12 (Dropout)<br>v2d_33[0][0]           | (None, 128, 128, 32) | 0       | con |
| conv2d_34 (Conv2D)<br>pout_12[0][0]            | (None, 128, 128, 32) | 9248    | dro |
| max_pooling2d_2 (MaxPooling2D)<br>v2d_34[0][0] | (None, 64, 64, 32)   | 0       | con |
| conv2d_35 (Conv2D)<br>_pooling2d_2[0][0]       | (None, 64, 64, 64)   | 18496   | max |
| dropout_13 (Dropout)<br>v2d_35[0][0]           | (None, 64, 64, 64)   | 0       | con |
| conv2d_36 (Conv2D)<br>pout_13[0][0]            | (None, 64, 64, 64)   | 36928   | dro |
| max_pooling2d_3 (MaxPooling2D)<br>v2d_36[0][0] | (None, 32, 32, 64)   | 0       | con |
| conv2d_37 (Conv2D)<br>_pooling2d_3[0][0]       | (None, 32, 32, 128)  | 73856   | max |

|  |                     |        |     |
|--|---------------------|--------|-----|
| dropout_14 (Dropout)<br>v2d_37[0][0]                 | (None, 32, 32, 128) | 0      | con |
| conv2d_38 (Conv2D)<br>pout_14[0][0]                  | (None, 32, 32, 128) | 147584 | dro |
| max_pooling2d_4 (MaxPooling2D)<br>v2d_38[0][0]       | (None, 16, 16, 128) | 0      | con |
| conv2d_39 (Conv2D)<br>_pooling2d_4[0][0]             | (None, 16, 16, 256) | 295168 | max |
| dropout_15 (Dropout)<br>v2d_39[0][0]                 | (None, 16, 16, 256) | 0      | con |
| conv2d_40 (Conv2D)<br>pout_15[0][0]                  | (None, 16, 16, 256) | 590080 | dro |
| conv2d_transpose_1 (Conv2DTrans<br>v2d_40[0][0]      | (None, 32, 32, 128) | 131200 | con |
| concatenate_1 (Concatenate)<br>v2d_transpose_1[0][0] | (None, 32, 32, 256) | 0      | con |
| v2d_38[0][0]   |                     |        | con |
| conv2d_41 (Conv2D)<br>catenate_1[0][0]               | (None, 32, 32, 128) | 295040 | con |
| dropout_16 (Dropout)<br>v2d_41[0][0]                 | (None, 32, 32, 128) | 0      | con |
| conv2d_42 (Conv2D)<br>pout_16[0][0]                  | (None, 32, 32, 128) | 147584 | dro |
| conv2d_transpose_2 (Conv2DTrans<br>v2d_42[0][0]      | (None, 64, 64, 64)  | 32832  | con |
| concatenate_2 (Concatenate)<br>v2d_transpose_2[0][0] | (None, 64, 64, 128) | 0      | con |
| v2d_36[0][0]   |                     |        | con |
| conv2d_43 (Conv2D)<br>catenate_2[0][0]               | (None, 64, 64, 64)  | 73792  | con |

|  |                      |       |     |
|--|----------------------|-------|-----|
| dropout_17 (Dropout)<br>v2d_43[0][0]                 | (None, 64, 64, 64)   | 0     | con |
| conv2d_44 (Conv2D)<br>pout_17[0][0]                  | (None, 64, 64, 64)   | 36928 | dro |
| conv2d_transpose_3 (Conv2DTrans<br>v2d_44[0][0]      | (None, 128, 128, 32) | 8224  | con |
| concatenate_3 (Concatenate)<br>v2d_transpose_3[0][0] | (None, 128, 128, 64) | 0     | con |
| v2d_34[0][0]   |                      |       | con |
| conv2d_45 (Conv2D)<br>catenate_3[0][0]               | (None, 128, 128, 32) | 18464 | con |
| dropout_18 (Dropout)<br>v2d_45[0][0]                 | (None, 128, 128, 32) | 0     | con |
| conv2d_46 (Conv2D)<br>pout_18[0][0]                  | (None, 128, 128, 32) | 9248  | dro |
| conv2d_transpose_4 (Conv2DTrans<br>v2d_46[0][0]      | (None, 256, 256, 16) | 2064  | con |
| concatenate_4 (Concatenate)<br>v2d_transpose_4[0][0] | (None, 256, 256, 32) | 0     | con |
| v2d_32[0][0]   |                      |       | con |
| conv2d_47 (Conv2D)<br>catenate_4[0][0]               | (None, 256, 256, 16) | 4624  | con |
| dropout_19 (Dropout)<br>v2d_47[0][0]                 | (None, 256, 256, 16) | 0     | con |
| conv2d_48 (Conv2D)<br>pout_19[0][0]                  | (None, 256, 256, 16) | 2320  | dro |
| conv2d_49 (Conv2D)<br>v2d_48[0][0]                   | (None, 256, 256, 1)  | 17    | con |
| =====  |                      |       |     |
| Total params: 1,941,105                              |                      |       |     |
| Trainable params: 1,941,105                          |                      |       |     |
| Non-trainable params: 0                              |                      |       |     |

Train on 603 samples, validate on 67 samples

Epoch 1/50

603/603 [=====] - 456s 756ms/step - loss:  
0.4283 - mean\_iou: 0.4303 - val\_loss: 0.3085 - val\_mean\_iou: 0.4616

Epoch 00001: val\_loss improved from inf to 0.30852, saving model to  
model-benchmark\_50.h5

Epoch 2/50

603/603 [=====] - 449s 745ms/step - loss:  
0.2091 - mean\_iou: 0.4974 - val\_loss: 0.1313 - val\_mean\_iou: 0.5473

Epoch 00002: val\_loss improved from 0.30852 to 0.13128, saving model  
to model-benchmark\_50.h5

Epoch 3/50

603/603 [=====] - 451s 748ms/step - loss:  
0.1196 - mean\_iou: 0.5842 - val\_loss: 0.1033 - val\_mean\_iou: 0.6183

Epoch 00003: val\_loss improved from 0.13128 to 0.10331, saving model  
to model-benchmark\_50.h5

Epoch 4/50

603/603 [=====] - 450s 746ms/step - loss:  
0.1102 - mean\_iou: 0.6422 - val\_loss: 0.1019 - val\_mean\_iou: 0.6617

Epoch 00004: val\_loss improved from 0.10331 to 0.10187, saving model  
to model-benchmark\_50.h5

Epoch 5/50

603/603 [=====] - 448s 744ms/step - loss:  
0.0994 - mean\_iou: 0.6781 - val\_loss: 0.1016 - val\_mean\_iou: 0.6912

Epoch 00005: val\_loss improved from 0.10187 to 0.10159, saving model  
to model-benchmark\_50.h5

Epoch 6/50

603/603 [=====] - 449s 744ms/step - loss:  
0.0920 - mean\_iou: 0.7022 - val\_loss: 0.0990 - val\_mean\_iou: 0.7129

Epoch 00006: val\_loss improved from 0.10159 to 0.09902, saving model  
to model-benchmark\_50.h5

Epoch 7/50

603/603 [=====] - 450s 746ms/step - loss:  
0.0872 - mean\_iou: 0.7219 - val\_loss: 0.0990 - val\_mean\_iou: 0.7298

Epoch 00007: val\_loss improved from 0.09902 to 0.09897, saving model  
to model-benchmark\_50.h5

Epoch 8/50

603/603 [=====] - 450s 747ms/step - loss:  
0.0861 - mean\_iou: 0.7370 - val\_loss: 0.1092 - val\_mean\_iou: 0.7430

Epoch 00008: val\_loss did not improve

Epoch 9/50

603/603 [=====] - 450s 745ms/step - loss:  
0.0823 - mean\_iou: 0.7482 - val\_loss: 0.0842 - val\_mean\_iou: 0.7537

Epoch 00009: val\_loss improved from 0.09897 to 0.08420, saving model  
to model-benchmark\_50.h5

Epoch 10/50

603/603 [=====] - 450s 747ms/step - loss:  
0.0809 - mean\_iou: 0.7584 - val\_loss: 0.0968 - val\_mean\_iou: 0.7627

Epoch 00010: val\_loss did not improve

Epoch 11/50

603/603 [=====] - 452s 749ms/step - loss:

0.0800 - mean\_iou: 0.7662 - val\_loss: 0.0879 - val\_mean\_iou: 0.7701

Epoch 00011: val\_loss did not improve

Epoch 12/50

603/603 [=====] - 452s 749ms/step - loss:  
0.0787 - mean\_iou: 0.7736 - val\_loss: 0.0933 - val\_mean\_iou: 0.7767

Epoch 00012: val\_loss did not improve

Epoch 13/50

603/603 [=====] - 451s 748ms/step - loss:  
0.0847 - mean\_iou: 0.7795 - val\_loss: 0.0855 - val\_mean\_iou: 0.7817

Epoch 00013: val\_loss did not improve

Epoch 14/50

603/603 [=====] - 451s 748ms/step - loss:  
0.0781 - mean\_iou: 0.7842 - val\_loss: 0.0794 - val\_mean\_iou: 0.7864

Epoch 00014: val\_loss improved from 0.08420 to 0.07944, saving model  
to model-benchmark\_50.h5

Epoch 15/50

603/603 [=====] - 453s 751ms/step - loss:  
0.0762 - mean\_iou: 0.7884 - val\_loss: 0.0902 - val\_mean\_iou: 0.7906

Epoch 00015: val\_loss did not improve

Epoch 16/50

603/603 [=====] - 451s 747ms/step - loss:  
0.0746 - mean\_iou: 0.7927 - val\_loss: 0.0853 - val\_mean\_iou: 0.7945

Epoch 00016: val\_loss did not improve

Epoch 17/50

603/603 [=====] - 448s 743ms/step - loss:  
0.0739 - mean\_iou: 0.7962 - val\_loss: 0.0749 - val\_mean\_iou: 0.7980

Epoch 00017: val\_loss improved from 0.07944 to 0.07494, saving model  
to model-benchmark\_50.h5

Epoch 18/50

603/603 [=====] - 452s 749ms/step - loss:  
0.0738 - mean\_iou: 0.7997 - val\_loss: 0.0680 - val\_mean\_iou: 0.8012

Epoch 00018: val\_loss improved from 0.07494 to 0.06797, saving model  
to model-benchmark\_50.h5

Epoch 19/50

603/603 [=====] - 451s 748ms/step - loss:  
0.0737 - mean\_iou: 0.8026 - val\_loss: 0.0765 - val\_mean\_iou: 0.8042

Epoch 00019: val\_loss did not improve

Epoch 20/50

603/603 [=====] - 451s 749ms/step - loss:  
0.0727 - mean\_iou: 0.8055 - val\_loss: 0.0664 - val\_mean\_iou: 0.8068

Epoch 00020: val\_loss improved from 0.06797 to 0.06639, saving model  
to model-benchmark\_50.h5

Epoch 21/50

603/603 [=====] - 450s 746ms/step - loss:  
0.0758 - mean\_iou: 0.8081 - val\_loss: 0.0802 - val\_mean\_iou: 0.8091

Epoch 00021: val\_loss did not improve

Epoch 22/50

603/603 [=====] - 449s 745ms/step - loss:  
0.0907 - mean\_iou: 0.8100 - val\_loss: 0.0989 - val\_mean\_iou: 0.8101

Epoch 00022: val\_loss did not improve

Epoch 23/50

603/603 [=====] - 450s 747ms/step - loss: 0.0830 - mean\_iou: 0.8105 - val\_loss: 0.0736 - val\_mean\_iou: 0.8113

Epoch 00023: val\_loss did not improve

Epoch 24/50

603/603 [=====] - 450s 747ms/step - loss: 0.1630 - mean\_iou: 0.8085 - val\_loss: 0.1083 - val\_mean\_iou: 0.8069

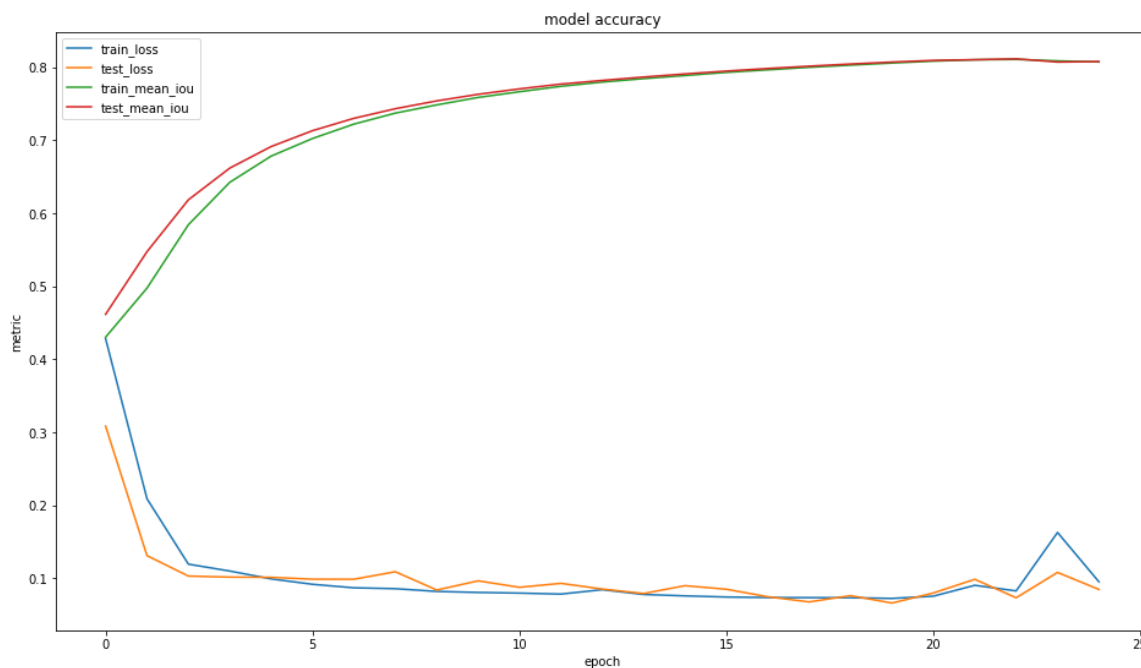
Epoch 00024: val\_loss did not improve

Epoch 25/50

603/603 [=====] - 450s 746ms/step - loss: 0.0954 - mean\_iou: 0.8070 - val\_loss: 0.0850 - val\_mean\_iou: 0.8075

Epoch 00025: val\_loss did not improve

Epoch 00025: early stopping



The Unet model using the original data was trained in 11271.82

The Unet model using the original data was trained in 11271.82 seconds. We can see that training and test loss decreased while the mean\_iou for both datasets increased steadily.

### Train the model with augmented data

In [12]:

```
# create model
model = u_net()

earlystopper = EarlyStopping(patience=5, verbose=1)
checkpointer = ModelCheckpoint('model-dsbowl2018-50epochs_augF.h5', verbose=1, save_best_only=True)

train_generator, test_generator = generator()

start = time.time()
model.fit_generator(train_generator,
                    steps_per_epoch=2000 // batch_size,
                    epochs=30,
                    validation_data=test_generator,
                    validation_steps=800 // batch_size,
                    verbose=1,
                    callbacks = [earlystopper, checkpointer])

end = time.time()
delta = end - start
print('The Unet model using the augmented data was trained in {:.6.2f} seconds'.format(delta))
```



| Layer (type)<br>connected to                  | Output Shape         | Param # | Con |
|---|----------------------|---------|-----|
| input_1 (InputLayer)                          | (None, 256, 256, 3)  | 0       |     |
| conv2d_1 (Conv2D)<br>input_1[0][0]            | (None, 256, 256, 16) | 448     | inp |
| dropout_1 (Dropout)<br>v2d_1[0][0]            | (None, 256, 256, 16) | 0       | con |
| conv2d_2 (Conv2D)<br>pout_1[0][0]             | (None, 256, 256, 16) | 2320    | dro |
| max_pooling2d_1 (MaxPooling2D)<br>v2d_2[0][0] | (None, 128, 128, 16) | 0       | con |
| conv2d_3 (Conv2D)<br>_pooling2d_1[0][0]       | (None, 128, 128, 32) | 4640    | max |
| dropout_2 (Dropout)<br>v2d_3[0][0]            | (None, 128, 128, 32) | 0       | con |
| conv2d_4 (Conv2D)<br>pout_2[0][0]             | (None, 128, 128, 32) | 9248    | dro |
| max_pooling2d_2 (MaxPooling2D)<br>v2d_4[0][0] | (None, 64, 64, 32)   | 0       | con |
| conv2d_5 (Conv2D)<br>_pooling2d_2[0][0]       | (None, 64, 64, 64)   | 18496   | max |
| dropout_3 (Dropout)<br>v2d_5[0][0]            | (None, 64, 64, 64)   | 0       | con |
| conv2d_6 (Conv2D)<br>pout_3[0][0]             | (None, 64, 64, 64)   | 36928   | dro |
| max_pooling2d_3 (MaxPooling2D)<br>v2d_6[0][0] | (None, 32, 32, 64)   | 0       | con |
| conv2d_7 (Conv2D)<br>_pooling2d_3[0][0]       | (None, 32, 32, 128)  | 73856   | max |

|  |                     |        |     |
|--|---------------------|--------|-----|
| dropout_4 (Dropout)<br>v2d_7[0][0]                   | (None, 32, 32, 128) | 0      | con |
| conv2d_8 (Conv2D)<br>pout_4[0][0]                    | (None, 32, 32, 128) | 147584 | dro |
| max_pooling2d_4 (MaxPooling2D)<br>v2d_8[0][0]        | (None, 16, 16, 128) | 0      | con |
| conv2d_9 (Conv2D)<br>_pooling2d_4[0][0]              | (None, 16, 16, 256) | 295168 | max |
| dropout_5 (Dropout)<br>v2d_9[0][0]                   | (None, 16, 16, 256) | 0      | con |
| conv2d_10 (Conv2D)<br>pout_5[0][0]                   | (None, 16, 16, 256) | 590080 | dro |
| conv2d_transpose_1 (Conv2DTrans<br>v2d_10[0][0]      | (None, 32, 32, 128) | 131200 | con |
| concatenate_1 (Concatenate)<br>v2d_transpose_1[0][0] | (None, 32, 32, 256) | 0      | con |
| v2d_8[0][0]  |                     |        | con |
| conv2d_11 (Conv2D)<br>catenate_1[0][0]               | (None, 32, 32, 128) | 295040 | con |
| dropout_6 (Dropout)<br>v2d_11[0][0]                  | (None, 32, 32, 128) | 0      | con |
| conv2d_12 (Conv2D)<br>pout_6[0][0]                   | (None, 32, 32, 128) | 147584 | dro |
| conv2d_transpose_2 (Conv2DTrans<br>v2d_12[0][0]      | (None, 64, 64, 64)  | 32832  | con |
| concatenate_2 (Concatenate)<br>v2d_transpose_2[0][0] | (None, 64, 64, 128) | 0      | con |
| v2d_6[0][0]  |                     |        | con |
| conv2d_13 (Conv2D)<br>catenate_2[0][0]               | (None, 64, 64, 64)  | 73792  | con |

|  |                      |       |     |
|--|----------------------|-------|-----|
| dropout_7 (Dropout)<br>v2d_13[0][0]                  | (None, 64, 64, 64)   | 0     | con |
| conv2d_14 (Conv2D)<br>pout_7[0][0]                   | (None, 64, 64, 64)   | 36928 | dro |
| conv2d_transpose_3 (Conv2DTrans<br>v2d_14[0][0]      | (None, 128, 128, 32) | 8224  | con |
| concatenate_3 (Concatenate)<br>v2d_transpose_3[0][0] | (None, 128, 128, 64) | 0     | con |
| v2d_4[0][0]  |                      |       | con |
| conv2d_15 (Conv2D)<br>catenate_3[0][0]               | (None, 128, 128, 32) | 18464 | con |
| dropout_8 (Dropout)<br>v2d_15[0][0]                  | (None, 128, 128, 32) | 0     | con |
| conv2d_16 (Conv2D)<br>pout_8[0][0]                   | (None, 128, 128, 32) | 9248  | dro |
| conv2d_transpose_4 (Conv2DTrans<br>v2d_16[0][0]      | (None, 256, 256, 16) | 2064  | con |
| concatenate_4 (Concatenate)<br>v2d_transpose_4[0][0] | (None, 256, 256, 32) | 0     | con |
| v2d_2[0][0]  |                      |       | con |
| conv2d_17 (Conv2D)<br>catenate_4[0][0]               | (None, 256, 256, 16) | 4624  | con |
| dropout_9 (Dropout)<br>v2d_17[0][0]                  | (None, 256, 256, 16) | 0     | con |
| conv2d_18 (Conv2D)<br>pout_9[0][0]                   | (None, 256, 256, 16) | 2320  | dro |
| conv2d_19 (Conv2D)<br>v2d_18[0][0]                   | (None, 256, 256, 1)  | 17    | con |
| =====  |                      |       |     |
| Total params: 1,941,105                              |                      |       |     |
| Trainable params: 1,941,105                          |                      |       |     |
| Non-trainable params: 0                              |                      |       |     |

Data was augmented in 12.16 seconds

Epoch 1/30

125/125 [=====] - 1669s 13s/step - loss: 0.1985 - mean\_iou: 0.5526 - val\_loss: 0.1372 - val\_mean\_iou: 0.6812

Epoch 00001: val\_loss improved from inf to 0.13721, saving model to model-dsbow12018-50epochs\_augF.h5

Epoch 2/30

125/125 [=====] - 1660s 13s/step - loss: 0.1003 - mean\_iou: 0.7230 - val\_loss: 0.0973 - val\_mean\_iou: 0.7520

Epoch 00002: val\_loss improved from 0.13721 to 0.09731, saving model to model-dsbow12018-50epochs\_augF.h5

Epoch 3/30

125/125 [=====] - 1662s 13s/step - loss: 0.0884 - mean\_iou: 0.7681 - val\_loss: 0.0861 - val\_mean\_iou: 0.7807

Epoch 00003: val\_loss improved from 0.09731 to 0.08611, saving model to model-dsbow12018-50epochs\_augF.h5

Epoch 4/30

125/125 [=====] - 1658s 13s/step - loss: 0.0812 - mean\_iou: 0.7899 - val\_loss: 0.0856 - val\_mean\_iou: 0.7969

Epoch 00004: val\_loss improved from 0.08611 to 0.08557, saving model to model-dsbow12018-50epochs\_augF.h5

Epoch 5/30

125/125 [=====] - 1662s 13s/step - loss: 0.0812 - mean\_iou: 0.8021 - val\_loss: 0.0834 - val\_mean\_iou: 0.8061

Epoch 00005: val\_loss improved from 0.08557 to 0.08338, saving model to model-dsbow12018-50epochs\_augF.h5

Epoch 6/30

125/125 [=====] - 1658s 13s/step - loss: 0.0767 - mean\_iou: 0.8098 - val\_loss: 0.0796 - val\_mean\_iou: 0.8128

Epoch 00006: val\_loss improved from 0.08338 to 0.07958, saving model to model-dsbow12018-50epochs\_augF.h5

Epoch 7/30

125/125 [=====] - 1658s 13s/step - loss: 0.0731 - mean\_iou: 0.8158 - val\_loss: 0.0848 - val\_mean\_iou: 0.8183

Epoch 00007: val\_loss did not improve

Epoch 8/30

125/125 [=====] - 1660s 13s/step - loss: 0.0712 - mean\_iou: 0.8206 - val\_loss: 0.0800 - val\_mean\_iou: 0.8229

Epoch 00008: val\_loss did not improve

Epoch 9/30

125/125 [=====] - 1661s 13s/step - loss: 0.0720 - mean\_iou: 0.8250 - val\_loss: 0.0763 - val\_mean\_iou: 0.8265

Epoch 00009: val\_loss improved from 0.07958 to 0.07627, saving model to model-dsbow12018-50epochs\_augF.h5

Epoch 10/30

125/125 [=====] - 1665s 13s/step - loss: 0.0711 - mean\_iou: 0.8279 - val\_loss: 0.0770 - val\_mean\_iou: 0.8292

Epoch 00010: val\_loss did not improve

Epoch 11/30

125/125 [=====] - 1661s 13s/step - loss: 0.0705 - mean\_iou: 0.8304 - val\_loss: 0.0752 - val\_mean\_iou: 0.8318

Epoch 00011: val\_loss improved from 0.07627 to 0.07523, saving model to model-dsbowl2018-50epochs\_augF.h5

Epoch 12/30

125/125 [=====] - 1665s 13s/step - loss: 0.0697 - mean\_iou: 0.8330 - val\_loss: 0.0726 - val\_mean\_iou: 0.8340

Epoch 00012: val\_loss improved from 0.07523 to 0.07262, saving model to model-dsbowl2018-50epochs\_augF.h5

Epoch 13/30

125/125 [=====] - 1665s 13s/step - loss: 0.0689 - mean\_iou: 0.8349 - val\_loss: 0.0753 - val\_mean\_iou: 0.8360

Epoch 00013: val\_loss did not improve

Epoch 14/30

125/125 [=====] - 1660s 13s/step - loss: 0.0722 - mean\_iou: 0.8370 - val\_loss: 0.1201 - val\_mean\_iou: 0.8366

Epoch 00014: val\_loss did not improve

Epoch 15/30

125/125 [=====] - 1667s 13s/step - loss: 0.0859 - mean\_iou: 0.8356 - val\_loss: 0.0882 - val\_mean\_iou: 0.8357

Epoch 00015: val\_loss did not improve

Epoch 16/30

125/125 [=====] - 1663s 13s/step - loss: 0.0747 - mean\_iou: 0.8361 - val\_loss: 0.0786 - val\_mean\_iou: 0.8367

Epoch 00016: val\_loss did not improve

Epoch 17/30

125/125 [=====] - 1661s 13s/step - loss: 0.0721 - mean\_iou: 0.8371 - val\_loss: 0.0758 - val\_mean\_iou: 0.8376

Epoch 00017: val\_loss did not improve

Epoch 00017: early stopping

The Unet model using the augmented data was trained in 28258.51 seconds

## Helper function to make Predictions

In [19]:

```

# helper function to calculate predictions
def calculate_predictions(file_name):
    start = time.time()
    print('Starting prediction with the {} model'.format(file_name))
    # Predict on test data using the previous model
    #model = load_model('model-dsbow12018-50epochs.h5', custom_objects={'mean_iou': mean_iou})
    model = load_model(file_name, custom_objects={'mean_iou': mean_iou})

    preds_test = model.predict(X_test, verbose=1)

    # Threshold predictions
    preds_test_t = (preds_test > 0.5).astype(np.uint8)

    # Create list of upsampled test masks
    preds_test_upsampled = []
    for i in range(len(preds_test)):
        preds_test_upsampled.append(resize(np.squeeze(preds_test[i]),
                                              (sizes_test[i][0], sizes_test[i][1]),
                                              mode='constant', preserve_range=True
        ))
    end = time.time()
    delta_time = end - start
    print('The prediction with the {} model took {:.62f} seconds'.format(file_name, delta_time))
    return preds_test_t, preds_test_upsampled

```

### Helper function to visualize a random image and its prediction

In [20]:

```

def visualize_test(preds_test_t, random_id):
    # this function takes two variables : the test prediction and random_id
    # random_id is the id of an image. It is either equal to an integer or to 'None'

    if random_id == 'None':
        ind = random.randint(0, len(preds_test_t))
    else:
        ind = random_id
    # Change the size of the plot
    plt.rcParams["figure.figsize"] = [16,9]
    # Draw two sets of images
    _, axarr = plt.subplots(1,2)
    axarr[0].imshow(X_test[ind])
    axarr[0].set_title("X_test["+str(ind)+"]")
    axarr[1].imshow(np.squeeze(preds_test_t[ind]))
    axarr[1].set_title("preds_test_t["+str(ind)+"]")
    plt.show()

```

### Helper function to encode

In [21]:

```
# Run-length encoding from https://www.kaggle.com/rakhlin/fast-run-length-encoding-python
def rle_encoding(x):
    # flatten the image (as per pixel convention) and keep the pixels where the mask is
    dots = np.where(x.T.flatten() == 1)[0]
    # define the lengths of the runs
    run_lengths = []
    # reset comparison point
    prev = -2
    for b in dots:
        # start a new pair for non-contiguous pixels
        if (b>prev+1):
            run_lengths.extend((b + 1, 0))
        # increase the run length of the last item in the list by 1
        run_lengths[-1] += 1
        # assign comparison point to the pixel in dots
        prev = b
    return run_lengths

def prob_to_rles(x, cutoff=0.5):
    # label image regions
    lab_img = label(x > cutoff)
    for i in range(1, lab_img.max() + 1):
        yield rle_encoding(lab_img == i)
```

In [22]:

```
# helper function to create test_ids and run length encoding
def new_test_ids(preds_test_upsampled):
    new_test_ids = []
    rles = []
    for n, id_ in enumerate(test_ids):
        rle = list(prob_to_rles(preds_test_upsampled[n]))
        rles.extend(rle)
        new_test_ids.extend([id_] * len(rle))
    return new_test_ids, rles
```

In [23]:

```
# Create submission DataFrame
def create_submission_dataframe(new_test_ids, rles, file_name):
    sub = pd.DataFrame()
    sub['ImageId'] = new_test_ids
    sub['EncodedPixels'] = pd.Series(rles).apply(lambda x: ' '.join(str(y) for y
in x))
    sub.to_csv(file_name, index=False)
```

## Make Predictions

In [28]:

```
# helper function to calculate predictions and create csv file
def predictions_csv(modele_name, modele_file, csv_file):
    random_id = 10

    print(modele_name)
    new_test_ids_ = []
    rles = []
    preds_test_t, preds_test_upsampled = calculate_predictions(modele_file)
    print('visualization with random image')
    visualize_test(preds_test_t, 'None')
    new_test_ids_, rles = new_test_ids(preds_test_upsampled)
    create_submission_dataframe(new_test_ids_, rles, csv_file)
    print('visualization with image number {}'.format(random_id))
    visualize_test(preds_test_t, random_id)

predictions_csv('Benchmark Model', 'model-benchmark_50.h5', 'model-benchmark_50.
csv')
print('\n')
predictions_csv('Unet Model with original data', 'model-dsbow12018-50epochsF.h5'
, 'model-dsbow12018-50epochsF.csv')
print('\n')
predictions_csv('Unet Model with augmented data', 'model-dsbow12018-50epochs_aug
F.h5', 'model-dsbow12018-50epochs_augF.csv')
```



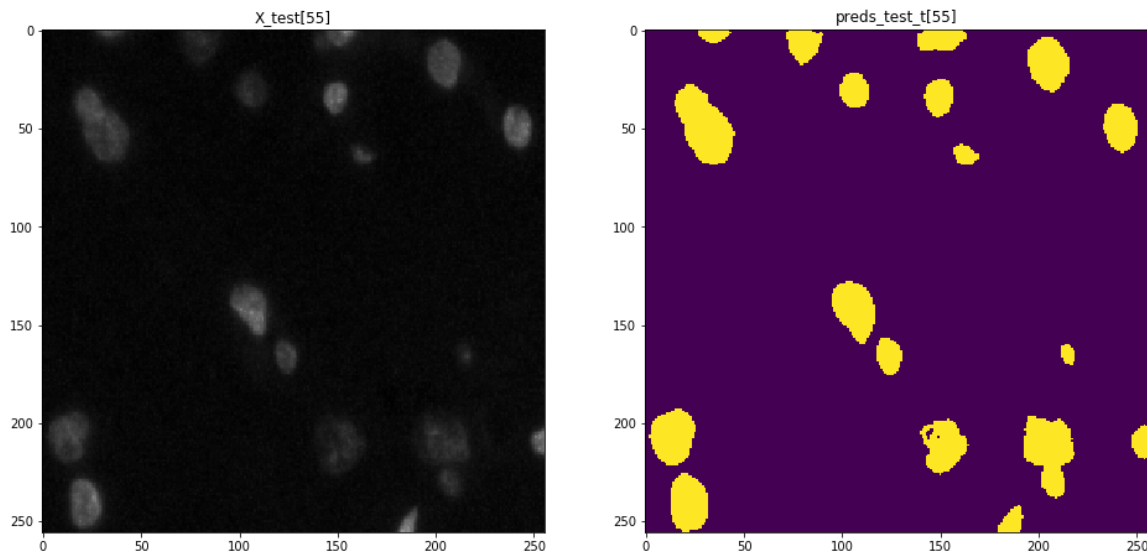
### Benchmark Model

Starting prediction with the model-benchmark\_50.h5 model

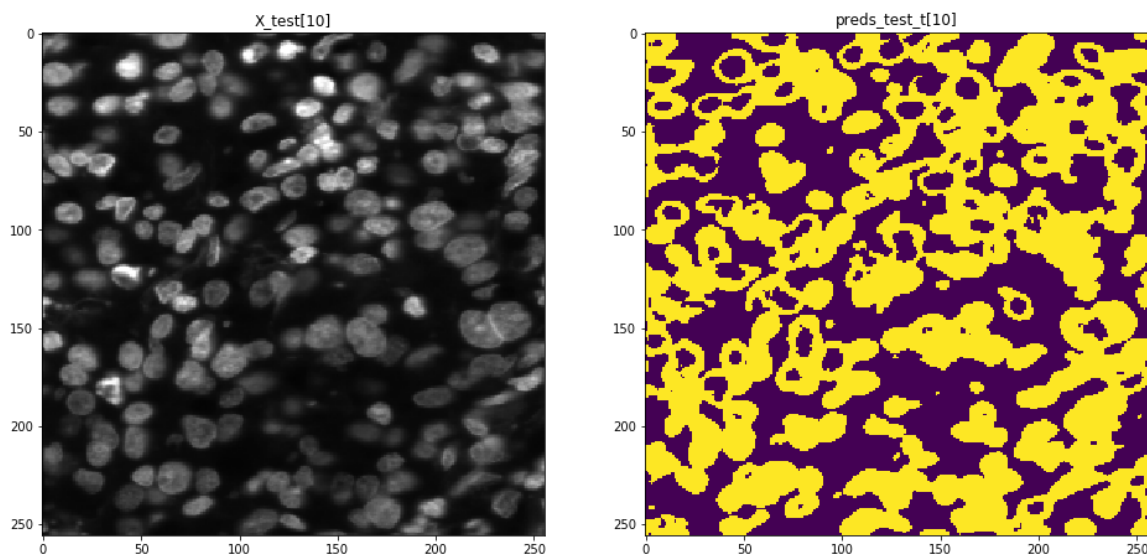
65/65 [=====] - 3s 40ms/step

The prediction with the model-benchmark\_50.h5 model took 32.56 seconds

visualization with random image



visualization with image number 10



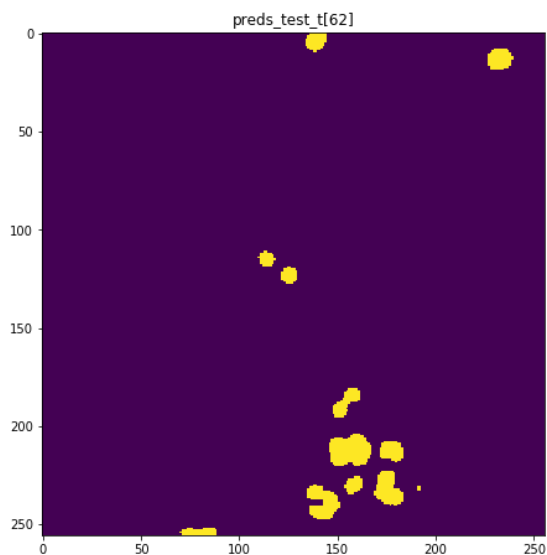
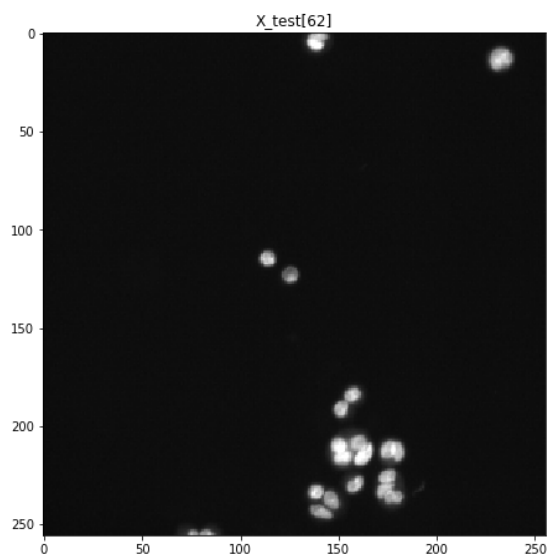
### Unet Model with original data

Starting prediction with the model-dsbow12018-50epochsF.h5 model

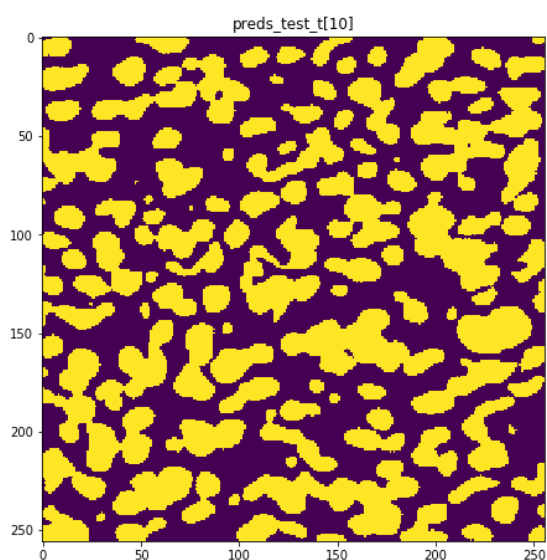
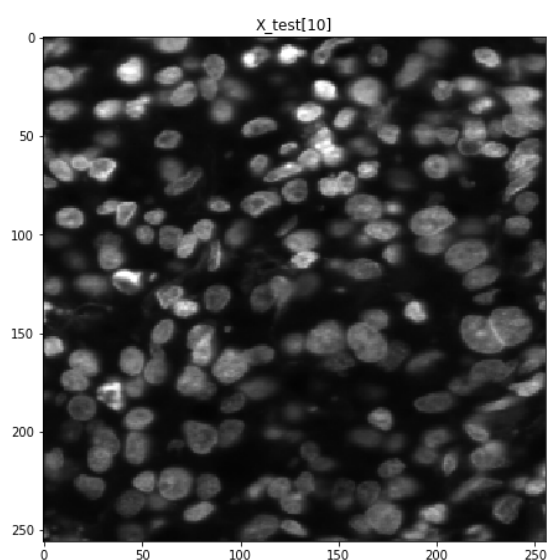
65/65 [=====] - 23s 358ms/step

The prediction with the model-dsbow12018-50epochsF.h5 model took 57.61 seconds

visualization with random image



visualization with image number 10

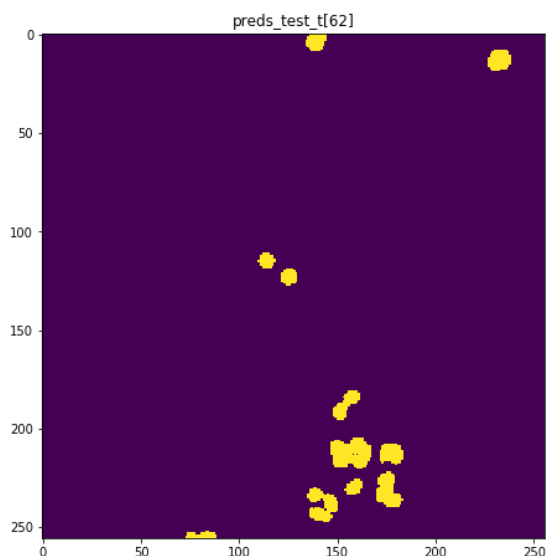
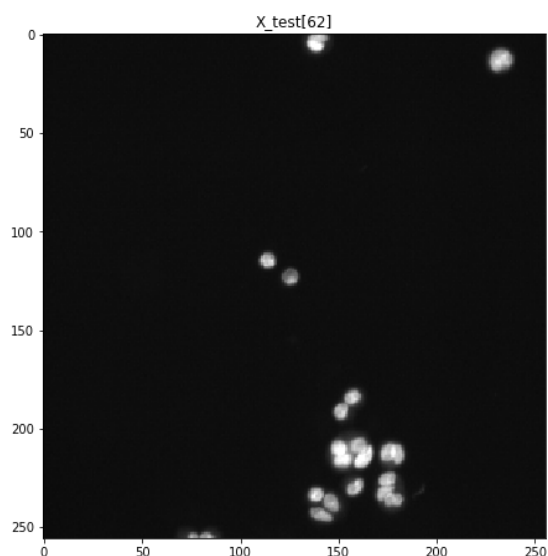


Unet Model with augmented data

Starting prediction with the model-dsbowl2018-50epochs\_augF.h5 model  
65/65 [=====] - 23s 349ms/step

The prediction with the model-dsbowl2018-50epochs\_augF.h5 model took  
60.69 seconds

visualization with random image



visualization with image number 10

