In [ ]:
```
!wget --header 'Host: storage.googleapis.com' --user-agent 'Mozilla/5.0 (X11; Ubuntu; Linux x86_64; rv:87.0) Gecko/20100
!pip install q keras==2.4.1
!pip install segmentation_models
!pip install tensorflow_io
!unzip '/content/ultrasound-nerve-segmentation.zip'
```

In [2]:
```
import os
import re
import random
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import re
import seaborn as sns
import cv2
from PIL import Image
from sklearn.model_selection import train_test_split, KFold
import tensorflow_io as tfio
import keras
import tensorflow as tf
# tf.compat.v1.enable_eager_execution()
from tensorflow import keras
from tensorflow.keras.layers import *
from tensorflow.keras.preprocessing import image
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.layers import UpSampling2D
from tensorflow.keras.layers import MaxPooling2D, GlobalAveragePooling2D
from tensorflow.keras.layers import concatenate,Dropout
from tensorflow.keras.layers import Multiply, MaxPooling2D, GlobalMaxPooling2D
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras import backend as K
from tensorflow.keras.layers import Input, Add, Dense, Activation, ZeroPadding2D
from tensorflow.keras.layers import BatchNormalization, Flatten, Conv2D, AveragePooling2D
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, ReduceLROnPlateau
from tensorflow.keras.utils import plot_model
from tensorflow.keras.initializers import glorot_uniform
from tensorflow.keras.optimizers import Adam
from keras.callbacks import ModelCheckpoint
import tensorflow
import keras
import cv2
import imgaug.augmenters as iaa
os.environ['TF_FORCE_GPU_ALLOW_GROWTH'] = 'true'
import segmentation_models as sm
from segmentation_models.metrics import iou_score
from segmentation_models import Unet
focal_loss = sm.losses.cce_dice_loss
import random
import segmentation_models as sm
from segmentation_models import Unet
# sm.set_framework('tf.keras')
tf.keras.backend.set_image_data_format('channels_last')
```

```
Using TensorFlow backend.
Segmentation Models: using `keras` framework.
```

In [3]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [58]:
```
#loading the dataframe containing images after removing conflicting images
df=pd.read_csv('/content/train_masks.csv')
img=pd.read_csv('/content/drive/MyDrive/dup_rem.csv')
img.drop('Unnamed: 0',axis=1,inplace=True)
img.image_name=img.image_name.astype(int)
img.subject_name=img.subject_name.astype(int)
img.columns=['image_path','img','subject','mask_path']
new_df=pd.merge(img,df,on=['img','subject'])
new_df.pixels.fillna(0,inplace=True)
val=[0 if i==0 else 1 for i in new_df.pixels]
new_df['mask_pres']=val
```

In [59]:
```
def cnn_generator(images, labels, is_training, batch_size=64):
    '''Construct a data generator using tf.Dataset'''

    def parse_function(filename,labels):
        #reading path
        image_string = tf.io.read_file(filename)
        #decoding image
        image = tfio.experimental.image.decode_tiff(image_string)

        # This will convert to float values in [0, 1]
        image = tf.image.convert_image_dtype(image, tf.float32)

        image = tf.image.resize(image, [im_height, im_width])
        return image,labels

    def flip_lr(image,labels):

        image = tf.image.flip_left_right(image)
```

```python
        return image,labels
    def flip_ud(image,labels):

        image = tf.image.flip_up_down(image)

        return image,labels

    def rotate(image,labels):
        val=tf.random.uniform(shape=[], minval=0, maxval=4, dtype=tf.int32)
        return tf.image.rot90(image, val),labels


    dataset = tf.data.Dataset.from_tensor_slices((images,labels))

    if is_training:
        dataset = dataset.shuffle(5000)  # depends on sample size

    # Transform and batch data at the same time
    dataset = dataset.apply(tf.data.experimental.map_and_batch( parse_function, batch_size,num_parallel_batches=4,  # cp
        drop_remainder=True if is_training else False))
    # augmentations = [flip,rotate]

    if is_training:
      if np.random.uniform(0,1)<0.1:
          dataset = dataset.map(flip_lr)
      elif np.random.uniform(0,1)<0.2:
          dataset = dataset.map(flip_ud)
      elif np.random.uniform(0,1)<0.3:
          dataset = dataset.map(rotate)
    dataset = dataset.repeat()

    dataset = dataset.prefetch(tf.data.experimental.AUTOTUNE)
    return dataset
```

In [60]:
```python
X_train, X_valid, y_train, y_valid = train_test_split(new_df.image_path, new_df.mask_pres, test_size=0.2, random_state=4
```

In [61]:
```python
im_height=128
im_width=128
tf.keras.backend.clear_session()
tr_cnn_generator = cnn_generator(X_train,y_train, is_training=True, batch_size=64)
val_cnn_generator = cnn_generator(X_valid,y_valid, is_training=False, batch_size=64)
```

In [62]:
```python
#using a pretrained network
base_model = keras.applications.InceptionResNetV2(
    weights='imagenet',  # Load weights pre-trained on ImageNet.
    input_shape=(128, 128, 3),
    include_top=False)
```

In [44]:
```python
base_model.trainable = False
```

In [63]:
```python
inp=Input((128,128,4))
conv1=Conv2D(filters=3,kernel_size=(3,3),padding='same')(inp)
base_model=base_model(conv1,training=False)
out = Flatten()(base_model)
out = Dense(1024, activation="relu")(out)
out = Dropout(0.5)(out)
out = Dense(1, activation="sigmoid")(out)
```

In [64]:
```python
model_clf = Model(inputs = inp, outputs = out)
```

In [101…
```python
from datetime import datetime
# logdir = "logs/scalars/" + datetime.now().strftime("%Y%m%d-%H%M%S")
# tensorboard_callback = keras.callbacks.TensorBoard(log_dir=logdir,histogram_freq=1, write_graph=True,write_grads=True)
callbacks = [
    ModelCheckpoint('best_model.h5', verbose=1, save_best_only=True, save_weights_only=False)
    ]
model_clf.compile(optimizer=Adam(lr=1e-8), loss='binary_crossentropy', metrics=['accuracy','AUC'])
```

In [54]:
```python
model_clf.summary()
```

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_4 (InputLayer)         [(None, 128, 128, 4)]     0
_________________________________________________________________
conv2d_407 (Conv2D)          (None, 128, 128, 3)       111
_________________________________________________________________
inception_resnet_v2 (Functio (None, 2, 2, 1536)        54336736
_________________________________________________________________
flatten_1 (Flatten)          (None, 6144)              0
_________________________________________________________________
dense_2 (Dense)              (None, 1024)              6292480
_________________________________________________________________
dropout_1 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 1025
=================================================================
Total params: 60,630,352
Trainable params: 60,569,808
Non-trainable params: 60,544
_________________________________________________________________
```

In [ ]:
```python
result_clf=model_clf.fit(tr_cnn_generator,steps_per_epoch=64,epochs=30,validation_data=val_cnn_generator,validation_step
```

```
Epoch 1/30
64/64 [==============================] - 64s 809ms/step - loss: 6.1494 - accuracy: 0.5266 - auc: 0.5153 - val_loss: 0.6346 - val_accuracy: 0.5958 - val_auc: 0.6949

Epoch 00001: val_loss improved from inf to 0.63464, saving model to best_model.h5
Epoch 2/30
64/64 [==============================] - 54s 852ms/step - loss: 0.6686 - accuracy: 0.5907 - auc: 0.6117 - val_loss: 0.6236 - val_accuracy: 0.6616 - val_auc: 0.7080

Epoch 00002: val_loss improved from 0.63464 to 0.62360, saving model to best_model.h5
Epoch 3/30
64/64 [==============================] - 55s 875ms/step - loss: 0.6273 - accuracy: 0.6468 - auc: 0.6938 - val_loss: 0.6069 - val_accuracy: 0.6830 - val_auc: 0.7301

Epoch 00003: val_loss improved from 0.62360 to 0.60689, saving model to best_model.h5
Epoch 4/30
64/64 [==============================] - 57s 888ms/step - loss: 0.6188 - accuracy: 0.6562 - auc: 0.7101 - val_loss: 0.5891 - val_accuracy: 0.6849 - val_auc: 0.7469

Epoch 00004: val_loss improved from 0.60689 to 0.58910, saving model to best_model.h5
Epoch 5/30
64/64 [==============================] - 55s 871ms/step - loss: 0.6086 - accuracy: 0.6611 - auc: 0.7139 - val_loss: 0.5847 - val_accuracy: 0.6857 - val_auc: 0.7508

Epoch 00005: val_loss improved from 0.58910 to 0.58467, saving model to best_model.h5
Epoch 6/30
64/64 [==============================] - 57s 889ms/step - loss: 0.6073 - accuracy: 0.6672 - auc: 0.7230 - val_loss: 0.5742 - val_accuracy: 0.7021 - val_auc: 0.7609

Epoch 00006: val_loss improved from 0.58467 to 0.57416, saving model to best_model.h5
Epoch 7/30
64/64 [==============================] - 56s 885ms/step - loss: 0.5874 - accuracy: 0.6896 - auc: 0.7499 - val_loss: 0.5668 - val_accuracy: 0.7063 - val_auc: 0.7794

Epoch 00007: val_loss improved from 0.57416 to 0.56679, saving model to best_model.h5
Epoch 8/30
64/64 [==============================] - 55s 861ms/step - loss: 0.5740 - accuracy: 0.7005 - auc: 0.7595 - val_loss: 0.5769 - val_accuracy: 0.6834 - val_auc: 0.7668

Epoch 00008: val_loss did not improve from 0.56679
Epoch 9/30
64/64 [==============================] - 50s 790ms/step - loss: 0.5950 - accuracy: 0.6804 - auc: 0.7398 - val_loss: 0.5742 - val_accuracy: 0.6925 - val_auc: 0.7758

Epoch 00009: val_loss did not improve from 0.56679
Epoch 10/30
64/64 [==============================] - 48s 760ms/step - loss: 0.5706 - accuracy: 0.7016 - auc: 0.7620 - val_loss: 0.5605 - val_accuracy: 0.7191 - val_auc: 0.7846

Epoch 00010: val_loss improved from 0.56679 to 0.56053, saving model to best_model.h5
Epoch 11/30
64/64 [==============================] - 48s 756ms/step - loss: 0.5589 - accuracy: 0.7007 - auc: 0.7804 - val_loss: 0.5734 - val_accuracy: 0.6957 - val_auc: 0.7792

Epoch 00011: val_loss did not improve from 0.56053
Epoch 12/30
64/64 [==============================] - 48s 753ms/step - loss: 0.5642 - accuracy: 0.7052 - auc: 0.7682 - val_loss: 0.5519 - val_accuracy: 0.7110 - val_auc: 0.7896

Epoch 00012: val_loss improved from 0.56053 to 0.55194, saving model to best_model.h5
Epoch 13/30
64/64 [==============================] - 48s 753ms/step - loss: 0.5557 - accuracy: 0.7179 - auc: 0.7831 - val_loss: 0.6152 - val_accuracy: 0.6525 - val_auc: 0.7805

Epoch 00013: val_loss did not improve from 0.55194
Epoch 14/30
64/64 [==============================] - 48s 750ms/step - loss: 0.5517 - accuracy: 0.7145 - auc: 0.7846 - val_loss: 0.5461 - val_accuracy: 0.7269 - val_auc: 0.7913

Epoch 00014: val_loss improved from 0.55194 to 0.54609, saving model to best_model.h5
Epoch 15/30
64/64 [==============================] - 48s 757ms/step - loss: 0.5474 - accuracy: 0.7204 - auc: 0.7912 - val_loss: 0.5632 - val_accuracy: 0.6979 - val_auc: 0.7911

Epoch 00015: val_loss did not improve from 0.54609
Epoch 16/30
64/64 [==============================] - 48s 748ms/step - loss: 0.5459 - accuracy: 0.7181 - auc: 0.7927 - val_loss: 0.5298 - val_accuracy: 0.7119 - val_auc: 0.8024

Epoch 00016: val_loss improved from 0.54609 to 0.52985, saving model to best_model.h5
Epoch 17/30
64/64 [==============================] - 48s 753ms/step - loss: 0.5614 - accuracy: 0.7139 - auc: 0.7821 - val_loss: 0.5530 - val_accuracy: 0.7284 - val_auc: 0.8066

Epoch 00017: val_loss did not improve from 0.52985
Epoch 18/30
64/64 [==============================] - 48s 750ms/step - loss: 0.5587 - accuracy: 0.7022 - auc: 0.7802 - val_loss: 0.5350 - val_accuracy: 0.7222 - val_auc: 0.8077

Epoch 00018: val_loss did not improve from 0.52985
Epoch 19/30
64/64 [==============================] - 48s 753ms/step - loss: 0.5449 - accuracy: 0.7160 - auc: 0.7962 - val_loss: 0.5359 - val_accuracy: 0.7198 - val_auc: 0.8041

Epoch 00019: val_loss did not improve from 0.52985
Epoch 20/30
64/64 [==============================] - 48s 753ms/step - loss: 0.5437 - accuracy: 0.7255 - auc: 0.7933 - val_loss: 0.5241 - val_accuracy: 0.7350 - val_auc: 0.8051

Epoch 00020: val_loss improved from 0.52985 to 0.52411, saving model to best_model.h5
Epoch 21/30
64/64 [==============================] - 48s 753ms/step - loss: 0.5424 - accuracy: 0.7198 - auc: 0.7943 - val_loss:
```

```
0.5350 - val_accuracy: 0.7289 - val_auc: 0.8060

Epoch 00021: val_loss did not improve from 0.52411
Epoch 22/30
64/64 [==============================] - 48s 748ms/step - loss: 0.5516 - accuracy: 0.7013 - auc: 0.7787 - val_loss:
0.5384 - val_accuracy: 0.7335 - val_auc: 0.8104

Epoch 00022: val_loss did not improve from 0.52411
Epoch 23/30
64/64 [==============================] - 47s 736ms/step - loss: 0.5465 - accuracy: 0.7117 - auc: 0.7904 - val_loss:
0.5444 - val_accuracy: 0.7257 - val_auc: 0.8075

Epoch 00023: val_loss did not improve from 0.52411
Epoch 24/30
64/64 [==============================] - 49s 747ms/step - loss: 0.5480 - accuracy: 0.7178 - auc: 0.7884 - val_loss:
0.5288 - val_accuracy: 0.7367 - val_auc: 0.8047

Epoch 00024: val_loss did not improve from 0.52411
Epoch 25/30
64/64 [==============================] - 49s 768ms/step - loss: 0.5246 - accuracy: 0.7293 - auc: 0.8095 - val_loss:
0.5121 - val_accuracy: 0.7490 - val_auc: 0.8185

Epoch 00025: val_loss improved from 0.52411 to 0.51205, saving model to best_model.h5
Epoch 26/30
64/64 [==============================] - 48s 759ms/step - loss: 0.5509 - accuracy: 0.7074 - auc: 0.7750 - val_loss:
0.5295 - val_accuracy: 0.7301 - val_auc: 0.8110

Epoch 00026: val_loss did not improve from 0.51205
Epoch 27/30
64/64 [==============================] - 48s 750ms/step - loss: 0.5175 - accuracy: 0.7302 - auc: 0.8135 - val_loss:
0.5342 - val_accuracy: 0.7335 - val_auc: 0.8089

Epoch 00027: val_loss did not improve from 0.51205
Epoch 28/30
64/64 [==============================] - 48s 754ms/step - loss: 0.5482 - accuracy: 0.7153 - auc: 0.7919 - val_loss:
0.5222 - val_accuracy: 0.7365 - val_auc: 0.8096

Epoch 00028: val_loss did not improve from 0.51205
Epoch 29/30
64/64 [==============================] - 48s 757ms/step - loss: 0.5166 - accuracy: 0.7417 - auc: 0.8138 - val_loss:
0.5167 - val_accuracy: 0.7439 - val_auc: 0.8112

Epoch 00029: val_loss did not improve from 0.51205
Epoch 30/30
64/64 [==============================] - 48s 755ms/step - loss: 0.5192 - accuracy: 0.7343 - auc: 0.8134 - val_loss:
0.5208 - val_accuracy: 0.7434 - val_auc: 0.8132

Epoch 00030: val_loss did not improve from 0.51205
```

In [109…

```
model_clf.load_weights('best_model.h5')
```

In [99]:

```
def classifier_generator(images):
    '''Data generator for inference phase'''
    image_string=tf.io.read_file(images)
    image = tfio.experimental.image.decode_tiff(image_string)
    image = tf.image.convert_image_dtype(image, tf.float32)
    image = tf.image.resize(image, [128, 128])
    return image
```

Prediction

In [73]:

```
#generating predictions on train and validation set
X_tr=np.zeros((len(X_train),128,128,4))
X_val=np.zeros((len(X_valid),128,128,4))
for i in range(len(X_train)):
  X_tr[i]=classifier_generator(X_train.iloc[i])
for i in range(len(X_valid)):
  X_val[i]=classifier_generator(X_valid.iloc[i])
pred_clf_tr=model_clf.predict(X_tr)
pred_clf_val=model_clf.predict(X_val)
```

In [106…

```
#using a default thresold of 0.5 for prediction
pred_clf_val=(np.array(pred_clf_val)>0.5)
pred_clf_tr=(np.array(pred_clf_tr)>0.5)
```

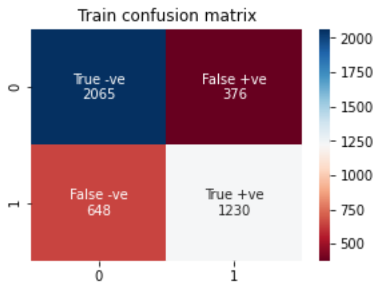
In [90]:

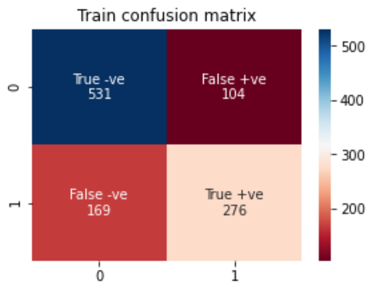
```
def Heatmapgen(x):
#https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30fea referred from here
  group_names = ['True -ve','False +ve','False -ve','True +ve']
  group_counts = ['{0:0.0f}'.format(value) for value in x.flatten()]
  labels = [f'{v1}\n{v2}' for v1, v2 in
  zip(group_names,group_counts)]
  labels = np.asarray(labels).reshape(2,2)
  sns.heatmap(x, annot=labels, fmt='', cmap='RdBu')
```

Getting number of false positives and false negatives

In [ ]:

```
#generating the confusion matrix
from sklearn.metrics import confusion_matrix
fig = plt.figure(figsize=(10,7))
ax1 = fig.add_subplot(221)
cf_matr1=confusion_matrix(y_train,pred_clf_tr_)
plt.title('Train confusion matrix')
Heatmapgen(cf_matr1)
ax2 = fig.add_subplot(222)
cf_matr2=confusion_matrix(y_valid,pred_clf_val_)
plt.title('Validation confusion matrix')
Heatmapgen(cf_matr2)
```




In [75]:
```
#storing the predictions in a list
pred_clf_val=[i[0] for i in pred_clf_val]
pred_clf_tr=[i[0] for i in pred_clf_tr]
```

Oversampling misclassified points

In [76]:
```
#getting the misclassified data points
wrng_pred=np.where(pred_clf_tr!=y_train,1,0)
#getting the indices..
wrng_pred=np.argwhere(wrng_pred)
wrng_pred=[i[0] for i in wrng_pred]
#out of misclassified datapoints randomly sampling 500 data points
smpl=random.sample(wrng_pred,500)
X_tr_smp=X_train.iloc[smpl]
y_tr_smp=y_train.iloc[smpl]
#oversampling the train set with misclassified datapoints
X_train_new=X_train.append(X_tr_smp)
y_train_new=y_train.append(y_tr_smp)
```

In [77]:
```
im_height=128
im_width=128
tf.keras.backend.clear_session()
tr_cnn_generator = cnn_generator(X_train_new,y_train_new, is_training=True, batch_size=64)
val_cnn_generator = cnn_generator(X_valid,y_valid, is_training=False, batch_size=64)
```

Retraining the model on oversampled points

In [110…
```
#retraining the model with oversampled data
result_clf=model_clf.fit(tr_cnn_generator,steps_per_epoch=64,epochs=20,validation_data=val_cnn_generator,validation_step
```

```
Epoch 11/20
64/64 [==============================] - 45s 690ms/step - loss: 0.4203 - accuracy: 0.7974 - auc: 0.8858 - val_loss:
0.4827 - val_accuracy: 0.7736 - val_auc: 0.8483

Epoch 00011: val_loss improved from inf to 0.48270, saving model to best_model.h5
Epoch 12/20
64/64 [==============================] - 44s 684ms/step - loss: 0.4264 - accuracy: 0.7917 - auc: 0.8829 - val_loss:
0.4828 - val_accuracy: 0.7726 - val_auc: 0.8485

Epoch 00012: val_loss did not improve from 0.48270
Epoch 13/20
64/64 [==============================] - 43s 676ms/step - loss: 0.4269 - accuracy: 0.7896 - auc: 0.8807 - val_loss:
0.4828 - val_accuracy: 0.7716 - val_auc: 0.8485

Epoch 00013: val_loss did not improve from 0.48270
Epoch 14/20
64/64 [==============================] - 43s 679ms/step - loss: 0.4263 - accuracy: 0.7893 - auc: 0.8825 - val_loss:
0.4828 - val_accuracy: 0.7716 - val_auc: 0.8486

Epoch 00014: val_loss did not improve from 0.48270
Epoch 15/20
64/64 [==============================] - 43s 676ms/step - loss: 0.4193 - accuracy: 0.7971 - auc: 0.8859 - val_loss:
0.4828 - val_accuracy: 0.7726 - val_auc: 0.8485

Epoch 00015: val_loss did not improve from 0.48270
Epoch 16/20
64/64 [==============================] - 43s 675ms/step - loss: 0.4219 - accuracy: 0.7908 - auc: 0.8845 - val_loss:
0.4829 - val_accuracy: 0.7716 - val_auc: 0.8485

Epoch 00016: val_loss did not improve from 0.48270
Epoch 17/20
64/64 [==============================] - 43s 678ms/step - loss: 0.4246 - accuracy: 0.7922 - auc: 0.8833 - val_loss:
0.4829 - val_accuracy: 0.7716 - val_auc: 0.8485

Epoch 00017: val_loss did not improve from 0.48270
Epoch 18/20
64/64 [==============================] - 45s 708ms/step - loss: 0.4346 - accuracy: 0.7834 - auc: 0.8760 - val_loss:
0.4829 - val_accuracy: 0.7714 - val_auc: 0.8485

Epoch 00018: val_loss did not improve from 0.48270
Epoch 19/20
64/64 [==============================] - 43s 677ms/step - loss: 0.4099 - accuracy: 0.8000 - auc: 0.8916 - val_loss:
0.4830 - val_accuracy: 0.7714 - val_auc: 0.8484

Epoch 00019: val_loss did not improve from 0.48270
Epoch 20/20
64/64 [==============================] - 43s 681ms/step - loss: 0.4224 - accuracy: 0.7954 - auc: 0.8847 - val_loss:
0.4829 - val_accuracy: 0.7726 - val_auc: 0.8485

Epoch 00020: val_loss did not improve from 0.48270
```

In [103…
```
#getting predictions using new model
X_tr=np.zeros((len(X_train),128,128,4))
```

```
X_val=np.zeros((len(X_valid),128,128,4))
for i in range(len(X_train)):
  X_tr[i]=classifier_generator(X_train.iloc[i])
for i in range(len(X_valid)):
  X_val[i]=classifier_generator(X_valid.iloc[i])
pred_clf_tr=model_clf.predict(X_tr)
pred_clf_val=model_clf.predict(X_val)
```

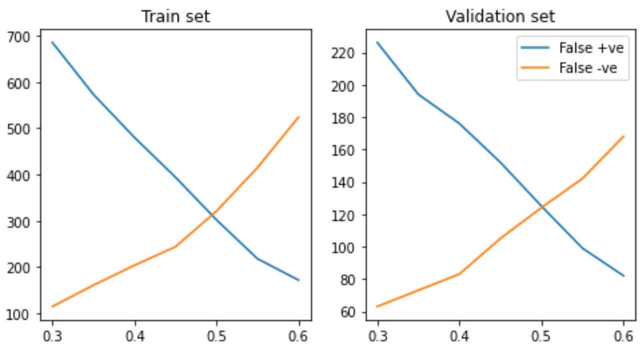
In [104…

```
#finding the best threshold on the newly trained model
#for this we calculate both the false positives and false negatives in the predictions
fp_arr_tr=[]
fn_arr_tr=[]
fp_arr_val=[]
fn_arr_val=[]
thresholds=[0.3,0.35,0.4,0.45,0.5,0.55,0.6]
for i in thresholds:
  pred_clf_val_=(np.array(pred_clf_val)>i)
  pred_clf_tr_=(np.array(pred_clf_tr)>i)
  cf_matr1=confusion_matrix(y_train,pred_clf_tr_)
  cf_matr2=confusion_matrix(y_valid,pred_clf_val_)
  fp_arr_tr.append(cf_matr1[0][1])
  fn_arr_tr.append(cf_matr1[1][0])
  fp_arr_val.append(cf_matr2[0][1])
  fn_arr_val.append(cf_matr2[1][0])
```

Trying various thresholds

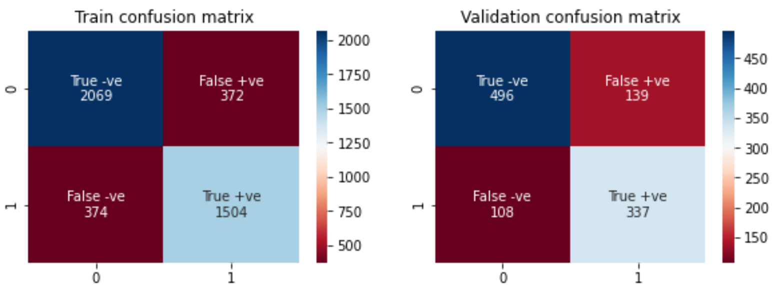
In [108…

```
#plotting the fp and fn in train and validation set
fig,ax=plt.subplots(1,2,figsize=(8,4))
ax[0].set_title('Train set')
ax[0].plot(thresholds,fp_arr_tr,label='False +ve')
ax[0].plot(thresholds,fn_arr_tr,label='False -ve')
ax[1].set_title('Validation set')
ax[1].plot(thresholds,fp_arr_val,label='False +ve')
ax[1].plot(thresholds,fn_arr_val,label='False -ve')
plt.legend()
plt.show()
```




In [91]:

```
#0.5
from sklearn.metrics import confusion_matrix
fig = plt.figure(figsize=(10,7))
ax1 = fig.add_subplot(221)
cf_matr1=confusion_matrix(y_train,pred_clf_tr)
plt.title('Train confusion matrix')
Heatmapgen(cf_matr1)
ax2 = fig.add_subplot(222)
cf_matr2=confusion_matrix(y_valid,pred_clf_val)
plt.title('Validation confusion matrix')
Heatmapgen(cf_matr2)
```




At threshold of 0.5 both fp and fn were together miniimum..